UNIVERSITY OF KWAZULU-NATAL

INYUVESI YAKWAZULU-NATALI

EEG ARTEFACT IDENTIFICATION AND EXTRACTION IN AUTONOMIC WIRELESS NETWORK FOR FUTURE COORDINATION AND CONTROL OF SEMI-AUTONOMOUS SYSTEMS

Submitted By

Chiemela Onunka, BSc. Eng., MSc. Eng.

205512204

Supervisor: Prof. Glen Bright

Co-Supervisor: Dr. Riaan Stopforth

In fulfilment for the requirements for the degree of Doctor of Philosophy in Mechanical Engineering at the College of Agriculture, Engineering and Science, University of KwaZulu Natal.

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Book Chapters

- Onunka C., Bright G., Stopforth R., “Brainwave Variability Identification in Robotic Arm Control Strategy” Robot Intelligence Technology and Applications 2 in Advances in Intelligent Systems and Computing, Springer-Verlag, vol. 274, pg. 173-189, 2014.
- Onunka C. Bright G., Stopforth R., “Encoding/Decoding Expressive EEG Signal Variability using IAF/ASDM Technique towards EEG Controlled Robotic System Development” submitted for publication in Machine Vision and Mechatronics in Practice, 2014.

Journal Papers

- Onunka C., Bright G., Stopforth R., “Wireless Autonomic Neural Network in EEG Signal Extraction Management” International Journal of Computer Applications in Technology, vol. 50, No.1/2, 2014.
- Onunka C., Bright G., Stopforth R., “EEG Artefact Selection: Analysing the Forward Inverse Problem using Linear Discrimination Kernels with Kaczmarz and ART Technique” Submitted to the Scientific World Journal on Recent Advancements in Soft Computing and Its Application, 2014

Conference Papers

- Onunka C., Bright G., Stopforth R., “Complex Augmentation in Autonomic EEG-Cayley Neural Network”. Accepted for publication in the proceedings of the 13th International Conference on Control, Automation, Robotics and Vision (ICARCV2014), Singapore, December 2014.
- Onunka C., Bright G., Stopforth R., “Investigating the Choice Factors on the Use of Xbee/Bluetooth as the Communication Scheme in EEG Sensor Networks” 6th Robotic & Mechatronics Conference of South Africa, RobMech 2013, UKZN, Durban, South Africa, October 2013.
- Onunka C. Bright G., Stopforth R “EEG Signal Variability Identification in Robotic Control Command Development” 2nd International Conference on Robot Intelligence Technology and Applications, RiTA2013, Denver, USA, December 2013.
- Onunka C., Bright G., Stopforth R. “EEG Extraction Management in Autonomic Neural Network” 19th International Conference on Machine Vision in Practice (M2VIP 2012), Auckland New Zealand, November 2012.

- Onunka C., Bright G. “Robotics and the Brain-Computer Interface System: Critical review for Manufacturing Application; 4th Robotics & Mechatronics Conference of South Africa, ROBMECH 2011, CSIR, Pretoria, South Africa, November, 2011.

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Dedication

This thesis is dedicated to my parents, Mr. and Mrs. C.O. Onunka for their care and immense support throughout the program. To my brothers and sisters for their love and care; I am grateful. To God be the glory for his mercies.

Abstract

Electroencephalographic signals is used to show correlations between specific forms of cognitive activities and robotic hand motion. This research presents EEG artefact identification, extraction and classification for use in the development of a robotic hand. The findings from the study were used to control a robotic arm and develop a suitable communication network that has no dependence on the human nervous system communication pathways.

The research was focused at modelling bio-sensing and bio-monitoring feedback system using electroencephalographic (EEG) as the source signal. An EEG communication system was developed for implementation on the robotic hand developed by the Mechatronics and Robotics Research Group (MR^2G). Neuronal activities produce electrical signals on surface of scalp in human beings. EEG the raw material for robot command development was generated from the neuronal activities. Specific techniques were used in modelling the EEG analysis system for implementation on the robotic hand. The techniques used include the Radial Basis Function (RBF) neural network, Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Wavelet Packet Transform (WPT), Multilayer Perceptron Neural Network (MLPNN), Learning Vector Quantization (LVQ) neural network, Bayesian and probabilistic paradigms in developing the EEG artefact identification, extraction and classification model. These techniques were investigated and implemented in order to have an efficient EEG artefact identification and extraction system for controlling the robotic hand.

The main contribution of the research was the identification, extraction and classification of electroencephalographic (EEG) artefacts in controlling a robotic hand. The specific contribution made in the research included the development of augmented EEG signal and EEG artefact extraction process using mathematical models. The models were used to develop integrated coordination and control architecture for the robotic arm. The research also made significant contribution to the development of modular Brain-Computer Interface (BCI) communication network. The BCI was augmented in autonomic wireless neural network activated by various EEG artefacts. The robotic hand control command codes were developed and they were modular in their application strategy. This was consolidated with adequate software and hardware architecture which were reconfigurable and leveraged using neuro-symbolic behaviour language in controlling the robotic hand developed by the Mechatronic and Robotic Research Group (MR^2G).

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List of Acronyms and Abbreviations

AEP	Average Electrode Potential
ALS	Amyotrophic Lateral Sclerosis
ANN	Artificial Neural Networks
AON	Action Observation Network
ARMA	Auto-Regressive Moving Average
ARIMA	Auto-Regressive Integrative Moving Average
ASDM	Asynchronous Sigma-Delta Modulator
BCI	Brain Computer Interface
BER	Bit Error Rate
BMI	Brain Machine Interface
BOLD	Blood Oxygenated Level Dependent
CNV	Contingent Negative Variation
CSFP	Common Spatial Frequency Patterns
DARPA	Defence Advanced Research Projects Agency
DC	Direct Current
DIPS	Distributed Intelligent Processing System
DNI	Direct Neural Interface
ECG	Electrocardiographic
ECoG	Electrocorticography
EEG	Electroencephalography
EMG	Electromyography
ERD	Event-Related De-Synchronization
ERP	Event Related Potential
ERS	Event-Related Synchronization
EP	Evoked Potentials
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
fMRI	Functional Magnetic Resonance Imaging
GDRS	Dynamics Robotic Systems
GPU	Graphic Processing Unit
GSK	Glossokinetic
HMM	Hidden Markov Model
HMRCS	Human Mind Robotic Control System
IAF	Integrate-And-Fire

ICA	Independent Component Analysis
IEDs	Interictal Epileptiform Discharges
ISI	Inter-Stimulus Interval
LFP	Local Field Potential
LTP	Long-Term Potentiation
LVQ	Learning Vector Quantization
LDA	Linear Discriminant Analysis
MEG	Magnetoencephalography
MLP	Multi-Layer Perceptron
MPLNN	Multilayer Perceptron Neural Network
MI-BCI	Motor Imagery Brain-Computer Interface
MSE	Mean Square Error
NSL	Neuro-Symbolic Language
OSC	Open Sound Control
PCA	Principal Component Analysis
QoE	Quality of Experience
RAAM	Recursive Auto-Association Memories
RBF	Radial Basis Function
RBFNN	RBF Neural Network Classification
RIFD	Radio Frequency Identification Technology
RPC	Remote Procedure Calls
RT	Reaction Time
SNR	Signal-To-Noise Ratio
SVD	Singular Value Decomposition
SQR	Signal-To-Quantisation Ratio
TFR	Time-Frequency Representation
US	United States
WSN	Wireless Sensor Network

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CHAPTER ONE

Introduction

1.1 Research Rationale

The vision of having electronic devices with the capacity of responding to the state of human cognition can be realised. There are possibilities entrenched in the ability of human beings to interact with their immediate environment without using the nervous system's primary pathways. This has created new ways of interaction that can speed-up the response sequence of human sensor-effector systems. Adaptations of asynchronous EEG-based BCI to robotic applications enabled the use of non-invasive BCI for continuous control of wheelchair and other mechatronic systems [**1**]. Controlling lights, opening of doors and windows can be realistic through the use of non-invasive EEG-based BCI. Non-invasive BCI technology can be used to provide improved communication pathways for people who have dysfunctional motor capabilities. The new communication pathways are necessary for such individuals to communicate with their surrounding environment. The improved advancements in motor imagery have led to the development of motor-imagery-based online interactive brain-controlled switch. The motor-imagery development has wide range of possibilities for robotic applications [**2**]. Developing innovative and novel brain-computer interfaces for robotic applications requires the physiological combination of human brain and body. This requires the development and improvement of relevant efficiencies that exist between human beings and machine. Various divergent groups of techniques are employed in harnessing brain signals. These techniques enable simultaneous and multi-modal architectures that can be used to provide the necessary efficiency and interchange-ability [**3**].

EG signals with their associated recording technique have their advantages and disadvantages for augmentative communication. The relations are considered with reference to the longevity of the sensing device developed for chronic BCI system [**4**]. Progress in bio-molecular networks has been used in the development of micro bio-robots for different applications. These micro bio-robots function in the absence of stimuli for self-actuation. Micro bio-robot system consists of a self-actuation system developed from an electro-kinetic actuation system coupled with DC electric fields. Robots operations using biological systems have signalling networks that enable them to function in their functional environment [**5**]. The immense applications of BCI technology offered through the use of biosensors have necessitated various areas of research and development across the globe. Biosensor technology offers a new revolution in the field of robotics. Robot control and coordination applications through

EEG are envisaged to integrate different bio-physio-chemical phenomena taking place at neural dimensions [**6**].

Human Threading ^{TM} [**7**] plays a critical role in optimizing the opportunities and possibilities that exist in the interaction between humans and machines. Human Threading ^{TM} uses trans-disciplinary fields to develop beneficial master pieces suitable to both able persons, physically challenged and persons with motor dysfunctions. Various human cognition observations, finite state machines, neuro-anatomical structures and their associative relationships suggest that new artefacts can be extracted for robotic control from EEG. Human Threading ^{TM} allows for the identification of physiological inefficiencies that exist between human beings and machines. The identifications results in the creation of new artefacts and enhancement of existing technologies. Human Threading ^{TM} follows three recursive procedures in the identification of the relationships between human beings and machines. These procedures are:

- Specific human interactions with machine or device are observed.
- Additional efficient method of interaction between humans and machines are designed if necessary.
- Output for the new relationship with the least cost and greatest operational efficiency between human being and computing devices are provided.

The development of efficient BMI and integration of additional degrees of freedom in the interchange-ability of systems improves the integration of the BMI architectures. The challenges include the development of adequate high-dimensional neural control command and accurate signal interpretation by robotic and mechatronic devices [**8**]. EEG robotics introduced landmark robotic possibilities for individuals with lower and upper extremity dysfunctions. These individuals with lower and upper extremity impairments experience difficulties in the use of normal appliances and devices. They face heavy challenges in the use and utilisation of conventional equipment. Robotic gadgets which can be manipulated and controlled using neuronal signals in semi-autonomous and autonomous modes are much desired. Semi-autonomous or automatic mode in robotic hand control using brain signals and other bio-signals are necessary for users with severe neuro-motor injuries. This was driving the development of the robotic hand to the level where individuals without motor abnormalities would be able to use such devices. For example, the desire of operating sophisticated electronic devices by physically challenged individuals motivated for the development of robust navigation system for robotic wheelchairs [**9**].

1.2 Research Background

Significant advances in neuro-robotics, neuroscience, neuro-prosthetics, computer science and different neural research groups around the globe led to the development of Brain-Computer Interfaces (BCI). The aim was to provide direct communication and control links between the brain and the physical environment around us. Neural spikes can be translated into control commands to control robotic arms, mouse cursors on the computer screen and wheelchairs amongst other possible applications. Neuronal activities in the brain create electric fields that extend to the scalp where they display specific topographical distribution. These scalp potential maps can be measured accurately given that adequate electrodes cover the whole head surface. Electroencephalography (EEG) measures the spatial distribution of voltage fields on the scalp and their variation over time. Scalp EEG mapping provides electric source imaging which estimates the source distribution in the brain [**10**].The inceptions of spatial distribution of voltages on the scalp are as the results of excitatory fluctuations and inhibitory postsynaptic potentials. These potentials have their origin at the apical dendrites of pyramidal cells located at the outer layer of the cerebral cortex [**11**].

Electroencephalography includes the recording of the oscillations of the brain electric potentials recorded with the aid of electrodes placed on the human scalp. These potentials reveal the state of consciousness of the human mind and cognitive load. Several EEG measuring methods provide relevant information on the cognitive processes that are associated with active human memory, mental calculations and selective attention. EEG measured from the scalp provides very large-scale and robust measures of neocortical dynamic function[1] [**12**]. EEG provides the most direct means of measuring the dynamic processes that occur in the brain over short time scales. The brain processes information over such short time scales. EEG is very crucial in the analysis of human consciousness. EEG provides the necessary window though not a very clear one, to the processes and functions of certain parts of the brain. It provides insights into the upper section of the neo-cortex where scalp electrodes are placed [**13**]. EEG signals are the result of neural activity between the thalamus[2] and the cortex observed as rhythmic cycles in the scalp. The complex feedback processes that occur in the thalamus produce the rhythmicity that is observed in the scalp. The cortical rhythmicity results from the complex interplay that exists in the thalamo-cortical circuitry. The interplay occurs in the presence of both local and global cortico-cortical circuitry activities [**14**].

EEG data for robotic hand control and coordination can be achieved through the comprehensive understanding and characterisation of EEG signals. The characterisation of EEG signals prompted for adequate analysis tool. EEG signals can be adequately extracted, studied and classified for use in semi-

[1] Neocortical dynamic function is the process by which many neurons collectively interact to produce human consciousness [**13**].

[2] The thalamus is the central sub-cortical structure, which transmits signals to the cortical level and transmits signals between ascending and descending pathways into multiple other brain areas [**14**].

autonomous mechatronic applications by using adequate tools. For efficient management of EEG data, spread sheets are necessary for long-term EEG data recording. File handling allows for efficient utilization of the computer memory. Tabular representations of EEG data, chart customisation, signal processing, cluster analysis, computational matrix and algebraic operations can be carried out efficiently with spread sheets [**15**]. The critical issue in the use of EEG signals for robotic hand control was the understanding of the neural code and its associated characteristics. Hacking the neural code efficiently has been the central issue in the application of neuroscience in robotics and mechatronics. The temporal structure of the neural spike train has made it difficult to process brain data. Uncorrelated noise in the neural spike trains made the process difficult. This has prompted that Event-Related Potentials (ERP) be recovered experimentally from noise over repeated trials. Biologically realistic multiple constraints can be used to solve the issue of under determination of EEG signal. The multiple constraints on EEG data include cortical gain control mechanisms, relationships between cognitive functions, oscillations, synchrony of EEG signals and spontaneous EEG signal irregularity. The coincident detections, integrators of cortical neurons, the causal relationship between EEG signal oscillations and band fluctuations are inclusive in the multiple constraints [**16**].

1.3 Research Objectives

The objectives of this research were to:

- Research, decode and encode EEG signals in an adaptive neural network.
- Research and integrate EEG autonomic neural network structure model with action observation network.
- Research and design an augmented EEG extraction-classification model.
- Research and model EEG communication/EEG artefact mapping system using neuro- symbolic behaviour language.
- Research and use distributed intelligence processing system in managing EEG communication and information transfer in autonomic neural network.

1.4 Scientific Contributions of the Thesis

This section summarizes the main contributions in this thesis.

1.4.1 Brainwave Decoding Via IAF-ASDM in Adaptive EEG Neural Networks

Chapter 3 presents the contribution made in integrating Integrate-And-Fire (IAF), Asynchronous Sigma-Delta Modulator (ASDM), quantisation ratio in the digital coding and decoding of EEG signal. Signal sample rate, and correlated noise model were considered in the representation of EEG neural spike structure progression. These were used in the modelling of brainwave data within adaptive neural network. The contributions are presented in sections 3.2, section 3.3, section 3.4, section 3.5 and section 3.6. The contributions in chapter 3 are summarized as follows:

- EEG artefacts were identified using EEG signal processing model.
- Random brainwaves were spectrally shaped and coded using adaptive linear predictive model and EEG spectral structure.
- EEG signal were digitally coded and decoded using IAF-ASDM technique in partnership with Burg’s and Levinson-Durbin algorithm.

Through repeated trials, ERPs recovered from averaged noise signals generated temporal neural code with varying cognitive activity. The chapter also made contribution in brainwave coding through adaptive modelling of white noise. This yielded somatic neural signal which was encoded into the neural pulse sequence. The brainwave decoding was monitored through negative feedback system. The EEG signal quality and the adaptive network performance were observed through the EEG data bit rate as it provided direct relationship on the efficiency and responsiveness of the brainwave coding and decoding system. The work in this chapter was performed in order to investigate and validate the performance of ASDM and IAF models in decoding EEG signal for the control of a robotic hand.

1.4.2 Integrating Wireless Autonomic Neural Network with Action Observation Network in EEG Data Management

Chapter 4 presents the contribution made in augmenting wireless autonomic EEG neural network with action observation network. This was used in managing the extraction and transmission of EEG data. These are presented in section 4.2, section 4.3, and section 4.4. The contributions in chapter 4 are summarized as follows:

- Action Observation Network (AON) was used to translate observed human cognitions into motor codes required for the execution of robot motion movements. The motion codes were biologically tuned using EEG artefacts. The primary execution mechanism of the augmented system was the ability of the action observation network to respond human cognitive states.
- The wireless autonomic neural network utilized distributed network system in managing EEG data transmission complexities necessary for integration in the improved BCI system. The wireless autonomic neural network utilized distributed management task force system in ensuring common neural information model for the data transmission network. The performance results of the wireless autonomic neural network are presented in section 4.6 and evaluated using the network bit error rate.

The work presented in chapter four was performed in order to develop the desired motor control codes for controlling the robotic hand using AON and investigate the performance of the wireless autonomic neural network in transmitting the motor control codes.

1.4.3 EEG Artefact Identification, Extraction and Classification Modelling In Adaptive Neural Networks

Chapter 5 presents the contributions made in using adaptive neural network model in developing efficient EEG artefact identification, extraction and classification. The contributions in chapter 5 are summarised as follows:

- The neural network synapses were modelled as Finite Impulse Response filters (FIR).
- Bayesian principles were used in modelling the search, extraction and classification of EEG artefacts.
- The sub neural network models were integrated into the extraction, classification and EEG data management system. The sub neural network models included Radial Basis Function (RBF) neural network, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Singular Value Decomposition (SVD, Wavelet Packet Transform (WPT), Multilayer Perceptron Neural Network (MLPNN), Learning Vector Quantization (LVQ) and Bayesian probabilistic paradigms.
- The chapter concluded by proposing a hybrid system for EEG artefact extraction and classification in adaptive neural networks. The proposed EEG artefact identification and extraction model is presented in section 5.13.

The work presented in chapter 5 was performed in order to develop an efficient and integrated EEG artefact identification, extraction and classification system for the control of a robotic hand.

1.4.4 NSBL Modelling In Distributed Intelligence Processing System

Chapter 6 presents the contribution made in the trade-offs that exist in the modelling and design of robotic control systems using EEG artefact as the command control signal. The contributions in chapter 6 are summarised as follows:

- Complex transformations for motion execution mechanisms were integrated using the Neuro-Symbolic Behaviour Language (NSBL) for the expression of propositional logical inference.
- The logical inferences were translated into logically equivalent neural network and distributed intelligence behaviour processing system. These transformations were in the bid to resolve the trade-offs that exist in the modelling of the neuronal system. Trade-off resolution enabled robotic device control and the intelligent behaviour processing system management.

- Adaptive innate releasing mechanisms was developed and specifically intended for use in the control of behaviour based robotic system. The control signal source was from human cognitive state and brain signals. The behaviour based robotic system was characterised through the interaction that exist in human perception and the intended action. Adaptation of the behaviour based robotic system in a coherent manner to changes in the environment tested its adaptability to the desired motion functions.

The work presented in chapter 6 was performed in order to develop a specialised behaviour-based robotic hand control system which reacts to EEG artefacts.

1.5 Contextual Framework and Impact of the Research Application

The contextual framework and application of this research was centred on the development of the control system of a robotic hand using EEG signal. The Mechatronic and Robotic research Group (MR^2G) at the University of KwaZulu-Natal were engaged in the process of improving a robotic hand and a robotic palm. Both robotic systems are controlled using EEG signals. The work presented in this thesis enhanced the development of control system of the robotic arm a step further. The identification, extraction and classification of EEG artefacts as presented in this thesis ensured that the robotic arm was controlled efficiently through smooth movement of the hand using EEG. The development of the robotic hand has useful application and enhances the day to day activities of physically challenged persons. For example, an amputee can hold, pick or place an object using the robotic hand. The ability of an amputee to perform such simple tasks has significant impact of on the social cohesion and participation of such individuals.

1.6 Thesis Organisation

The thesis is organised as follows: chapter 1 provides an introduction to the study, the research rationale and background while highlighting the main contributions in the thesis. Chapter 2 presents a comprehensive review on human brain, electroencephalography, EEG activity types, EEG artefacts and the generation of brainwaves. Chapter 2 also discussed the various types of brainwaves obtainable for use in robotics and mechatronic systems. The influence of event related potentials on the generation of brainwaves are also discussed. The overviews on the various BCI systems, progress in BCI development, the importance of CNV and ERP are also discussed in chapter 2. Chapter 3 presents brainwave decoding and coding. The influence of IAF-ASDM on the brainwave decoding and encoding process is discussed. Chapter 4 presents wireless autonomic neural network and EEG data management system integrated with action observation network. EEG data extraction and transmission were discussed and EEG data management system was adequately modelled. Chapter 5 presents EEG data identification, extraction and classification in neural networks. Chapter 6 presents the development of neuro-symbolic behaviour language for semi-autonomous control applications. Chapter 7 presents various case study applications of EEG signal processing in BCI and BMI technology development. Chapter 8 concludes the thesis and presents future work on the research.

1.7 Summary

Chapter 1 provided an overview on the research carried out during study on EEG and its application to BCI, BMI, robotics, semi-autonomous and mechatronic systems. The chapter also provided summarized contributions made in the thesis and publications resulting from the study.

CHAPTER TWO

Literature Review

In this chapter, the review on electroencephalographic signal, BCI technology development, human brain structure and advancements made in the field of EEG robotics are presented. The chapter discussed the various types of EEG signals, EEG activity types. The chapter presented the importance of contingent negative variation and event related potential in EEG robotics and concludes with the various progresses made in invasive and non-invasive EEG technology towards the control and coordination of semi-autonomous mechatronic systems.

2.1 EEG and BCI Technology Development

Fundamental characteristic BCI behaviour was dependent on the critical development of the necessary foundation on clinical basis for identifying electrical activities occurring in the brain. Appreciation of normal waveform variations in brain signal and variants of normal brain signals may be of uncertain importance. Fluctuations of normal EEG signal in an individual are essential in providing accurate impressions for robotic and mechatronic applications. In situations where EEG signal abnormalities are in doubt, the conservative impression of "normal" was deemed adequate for further EEG signal interpretation, usage and application.

Motor recovery has been the critical issue in clinical rehabilitations. Patients with progressive ailments such as Amyotrophic Lateral Sclerosis (ALS), multiple sclerosis, Parkinson's disease, stroke, cerebral palsy, and injury to spinal cord are of interest. Restoration of normal activities and quality of life for patients with such diseases are important considerations. This has increased the search for more efficient and effective rehabilitation methods for individuals with motor disabilities. Developments made in BCI technology have increased the interest in improving the quality of life and restoration of motion function for people with severe motor disabilities. Critical techniques required by BCI technology can be used to facilitate rehabilitation in patients with severely impaired muscle control. This was carried out through the substitution of normal neuromuscular outputs. The process enabled an individual to interact with their environment through their brain signals instead of their muscles. The second critical technique necessary in the restoration of motor function required that activity-dependent brain plasticity actions are induced in order to restore normal brain function. This can also be deactivated through the deactivation of specific brain signals. Patients are trained to control these signals and computing capabilities are also improved through the training process. The process have enabled individuals with motor disabilities to effectively use their brain signals to communicate and control objects in their environments. These functional capacities of these individuals have enabled them to bypass their impaired neuromuscular system [**17**].

The primary aim of using BCI technology in robotics and mechatronic systems was to reduce the user's physical involvement in robotic and mechatronic device control. Robots propose and execute actions based on environmental data and cross checks each motion proposition against the intended human cognition. Decisive semi-autonomous navigation has been deemed necessary in the development of BCI technology. BCI technology development has created the platform where human beings can effectively interact with robots and electronic devices at certain degree of compatibility and control. The extraction of motion features and motion recognition can be viewed at probabilistic level to determine motion feature distribution over possible actions for the robot [**18**].

The need for real-time BCI systems was critical for control options that are available to paraplegic patients and for other robotic and mechatronic applications. Functional Magnetic Resonance Imaging (fMRI) has the ability to reveal neuronal activity with superior spatial localisation using non-invasive methods. Real-time fMRI allowed for feedbacks from region-specific brain activations in an individual. This empowered the individual to learn how to modulate brain functions involved in attention, emotions and perception of pain. These brain activities identified through fMRI can be translated into control commands for movement of robotic arm or fingers. Real-time fMRI can be used as the signal detector to ascertain the feasibility of using Blood Oxygenated Level Dependent (BOLD) signals originating from regions-of-interest. BOLD was regulated by the subject from the motor cortex to the movement of robotic arm. In this process, motor imagery tasks are utilised to ensure that only thought processes are used to control the robotic arm and not overt muscle movements [**19**].

Effective use of EEG in the field of robotics was rendered useless without the Brain-Computer Interface (BCI) or Brain Machine Interface (BMI). BCI allowed human beings to be able to control robotic systems by motor imagery electroencephalogram. BCI framework provided methods for feature extractions using Common Spatial Frequency Patterns (CSFP) with the aim of motor imagery electroencephalogram classifications. The goal of the BCI system[3] was to provide robotic control with short response time. The robotic control was based on subject-specific and object-specific adaptations of system parameters. Technological developments in the field of robotics have opened the doors that can make the dreams, desires and human cognitive processes come true [**20**]. BCI system enables the translation of human thoughts and intents by machines into robotic motions. Motivated by advancements in BCI technology systems, BCI-based robotic control is introduced and can be referred to as Human Mind Robotic Control System (HMRCS). The human mind robotic control system directly translates brain signals associated with motor neurons into commands for controlling robots. HMRCS

[3] BCI systems are devices that allow interaction between the brain and artificial devices.

bypasses the normal motor output neural pathways. Research has indicated that distinct brain signals such as Event-Related De-synchronization (ERD) or Event-Related Synchronization (ERS) are detectable from EEG signals. These can be detected for both imagined and real motor movements in human beings [**21**]. This advancement paved the way for the Motor Imagery Brain-Computer Interface (MI-BCI). MI-BCI translates the imagination of movements into commands and provides neural communication system for robotic control [**22**].

Robots, machines and mechatronic systems play very important roles in our everyday activities so long as movement and communication processes are involved. Robotic systems in constant interaction with their users are usually not cognitive of the internal state of their users. There was inadequate execution of actions, unnatural interaction and there are displays in inefficiencies on the part of the user. This was true for humanoid robots that are designed to improve the daily life of their users. The humanoid robots are expected to interact with their human users socially and empathetically. Human cognitive-based robotic system was able to adapt its motion pattern strategy to different brain patterns of its user. Brain patterns are classified using EEG signals and these patterns correspond to the level of activity and process that goes on in the brain. The robot responds to the information that matches detected patterns. The robot utilizes EEG signals recorded from the users brain activity patterns and adapt to this information strategy in serving the user's needs [**23**]. Quantitative techniques have been proposed for assessing human cognitive efforts, engagement and workload by observing the neurobiological mechanisms underlying EEG brain dynamics and ERPs [**24**]. ERP signals provide the necessary platform in establishing the relationship between various stimuli and human cognitive responses that corresponds to correct or incorrect motor reactions [**25**]. Cognitive monitoring system is embedded into the cognitive-base system providing real time measures of cognitive and affective state of the human mind [**26**]. Its extensive usage provides useful information in the monitoring of physiological, behavioural, contextual and situational data streaming from the brain [**27**].

EEG data can be classified into higher order and lower order variables. The lower order variables include behavioural and physiological data. The higher order variables include stress, auditory load, motor load, verbal load, spatial load, alertness and executive load. The outputs from these variables involve certain level of identification and tracking of on-going tasks. This was crucial in the prediction of human intention [**28**]. BCI system offers subjects the explicit capacity of controlling their own brain activity. This can also be done by using motor activity to generate signals that are able to communicate with robotic devices or computers. Recent findings in the various fields of neuroscience, neuro-robotics, biotechnology, neurophysiology and mechatronics have the tremendous benefit. The findings have significant on impact persons who are physically challenged and also for healthy individuals. The human brain is made up of large network of billions of neurons. Each neuron has several dendrites, a soma and an axon. The neurons are connected to each other through their axons and the point of contact between the axons and the dendrites is the synapses. The dendrites serve as input channels for information passage and the axons serve as output passage for the information. The displacement of polarized ions in the brain initiates the transmission of signals and electric fields are generated from action potentials from firing neurons [**29**]. Embedded in the electrically conducting medium are the neurons. The neuronal environment made up of extracellular fluid permits extracellular activity of a cell to be understood by the neighbouring cells. Extracellular potential is generated from fast and slow spiking activity of the neurons. The slow spiking activities are referred to as Local Field Potentials (LFPs). They represent the total electric activity of neurons and associated glia cells [**30**].

The use of EEG recordings has grown immensely in the field of medicine. The importance of EEG in engineering has attracted little emphasis in core engineering fields, especially in the field of robotics. Improvements in technological know-how have improved the recording and storage of EEG signals. This progress has reached certain limits in relation to accuracy and the number of derivations recorded simultaneously. The first application of signal processing techniques to EEG can be traced as far back as 1932, where Fourier analysis was applied to short EEG readings [**31**]. The digital storage of the EEG time series created the platform for signal processing applications in various engineering fields, robotics and mathematical analysis [**32**]. It has been demonstrated that hippocampal EEG[4] signals have direct correlation to cognitive processes and behaviours such as attention, voluntary movement and learning [**33**].

Electrical brain stimulation on human brain and rats has been used as the primary input source in providing virtual tactical cues and rewards. The process has been effectively used to instruct animals remotely in navigating them through complex mazes and environments [**34**]. Researchers developing BCIs are trying to comprehend the complex information network of the brain, building and integrating artificial communication channels. The development of new communication channels for the brain increases the power of the brain. This was achieved to a certain extent by releasing the brain from innate limitations and constraints. This can make physically challenged individuals to be less challenged physically and healthy individuals more powerful. Communication intelligence systems are complex as the BCI technology expands their possibilities in the control and coordination of robotic systems [**35**].

2.2 Electroencephalography (EEG)

Electroencephalography is the unique and valuable method of measuring the brain's electrical functions in human beings. The process provides graphical display of difference in voltages from two sites of the brain recorded over time. EEG involves the study of recorded electrical signals generated by the brain. The recording process can be extra-cranial EEG recording or intracranial EEG recording. Extra-cranial EEG recording involves doing broad evaluation of the electro-cerebral activity in both hemispheres of

[4] Hippocampal EEG are recorded using hippocampal electrodes

the brain. Intracranial EEG stipulates the use of focused EEG recording directly from the brain with aid of electrodes implanted surgically into brain. These surgically implanted electrodes are directed and targeted at specific regions of the brain. The implants are able to detect information on focal cerebral dysfunction, the presence of Interictal Epileptiform Discharges (IEDs). Patterns that may be of special significance for special applications can also be detected by using implants. To understand the interpretation of an abnormal EEG, it is critical to understand the criteria crucial in the definition of normal EEG patterns. Normal EEG recording does not exclude robotic applications or clinical diagnosis. Abnormal findings on EEG recordings may be supportive or indicative of cerebral dysfunction which may be far from the reason of performing the recording. In recent times, it is the robotic and clinical applications of EEG results that imparts the usage and utility of EEG [**36**].

2.2.1 Artefacts

Variety of artefacts[5] may be observed and may be the consequence of mechanical, biological or instrumental sources. Individuals with unshielded electrodes act as an antenna and produce extra-cerebral sources thereby creating interference on the EEG recording. Artefacts are also the consequence of current flow in electrode depolarisation and are amplified by the amplifiers and generate noise in the recordings. Environmental artefacts may be quite difficult to observe. Environmental artefacts may often not be readily identifiable and correctable within the definitions of the hostile environment during an EEG recording. Telephone lines may interfere with EEG recording and produce an artefact that may be typically present in all EEG channels.

Wave groups produced by technical means or distractions which are not solely due to brain activity in the cerebral region may be regarded as artefacts. Artefacts may be grouped into two categories namely: There are physiological artefacts arising from sources other than the brain. There are also non-physiological artefacts arising from sources outside the human body. Physiological artefacts include: electromyographic artefacts (EMG), glossokinetic (GSK) artefact, eye movements, electrocardiographic (ECG) artefacts, pulse artefact and skin artefacts. The non-physiological artefacts include: electrodes and leads, alternating current, movement artefact and intravenous artefacts.

Eye movements appear in all EEG recordings. Eye movements include: vertical eye movement, downward eye movement, eye blinks, eye closures, eye flutter, eye opening, lateral eye movements and asymmetrical eye movements [**37**]. ECG artefacts are variations in EEG recordings in relation to the field of the heart potentials over the surface of the scalp. In general, individuals with short and wide necks have higher ECG artefact in their EEG recordings. Pulse artefact arises when the EEG electrode is positioned over pulsating blood vessel. Skin artefacts arise when sweats alter the electrode impedance and initiate artefacts in the EEG recordings. There are vast range of sources that generate non-

[5] The electrical signals observed from the brain or on the human body representing the EEG recording

physiological artefacts from the environment and also externally to the human neural system. These sources arise from within the EEG recording instruments, EEG recording electrodes and other environmental sources. Fixation instability in EEG electrode lead and high impedance generates external artefacts to EEG recordings. The fixation instabilities are usually as the result of changes in electrode junction potential. Insufficient grounding of electrodes may introduce external artefacts caused by higher impedance between the electrodes and the ground of the amplifier. Disturbance on the electrodes and leads causes artefact movement. Movements of the lead cause changes in capacitance and built-up charge dissipated into the EEG recordings are regarded as external artefacts [**37**]. In this study, artefacts are regarded as useful EEG signals or brainwaves that can be utilised in the semi-autonomous control of electronic and mechatronic devices.

2.3 EEG Rhythms

The various applications of EEG provide data on bio-signal generators resulting from the three-dimensional sphere with inference to location, distribution, waveform frequency morphology and polarity. The states of wakefulness are important features required for accurate interpretation of normal EEG signal. Human beings have EEG patterns comprising of brainwaves that vary in amplitude, frequency, distribution and location. EEG signals may vary with the state of consciousness of human beings. This subsection discusses the various EEG patterns and rhythms that are useful for robotics and mechatronics applications [**37**].

2.3.1 Alpha Rhythm

Alpha rhythms are the posterior dominant rhythms that are represented bilaterally over the posterior head regions and have the frequency range of 8-13 Hz. An alpha rhythm is attenuated by the opening of the eyes. Alpha rhythms are distributed maximally in the occipital regions and shifts anteriorly during drowsiness. Alpha rhythm is situated at the posterior half of the skull, found around the posterior temporal, parietal and occipital regions. Voltage asymmetries greater than 50% are regarded as abnormal. The unilateral failure of alpha rhythm to attenuation indicates that there is an ipsilateral abnormality[6]. At normal attenuation, there may be an alpha squeak[7] after the closure of the eyes. The variant forms of alpha rhythms include slow alpha which is one-half the normal alpha frequency and fast alpha which is two times the normal alpha frequency and also having similar distribution and reactivity. Another form of alpha rhythm is the paradoxical alpha which is the result of alertness instead of drowsiness [**36**]. Alpha rhythm has variable amplitude usually below 50 µV, best observed under relatively low mental activity. In general, alpha rhythm amplitude ranges from 20 µV -100 µV. Values above 100 µV are typically not observed in human beings. Alpha rhythm is usually attenuated or

[6] Ipsilateral abnormality of alpha rhythm is referred to as Bancaud's Phenomenon
[7] Alpha squeak is the transient increase of alpha frequencies immediately after closing the eye.

blocked by attention, visual and mental effort. Alpha rhythms have an average rhythm of 10 rhythms per second. An individual may produce paradoxical alpha rhythms while in full cognitive state. This occurs upon the opening of the eyes and facilitated the attenuation of alpha rhythms.

2.3.2 The Mu Rhythm

Mu rhythm is the centrally positioned aciform alpha frequency with the frequency range of 8 Hz to 10 Hz. It represents the activity of the sensorimotor cortex at rest. The mu rhythm resembles the alpha rhythm and does not get blocked with the opening of the eye. It demonstrates the contralateral movement of an extremity. The mu rhythm may be asymmetrical and asynchronous even in the absence of an adequate structural lesion. The mu rhythm has lower amplitude than the alpha rhythm and may be considered abnormal in the presence of focal slowing which may be persistent and un-reactive. The amplitude of mu rhythm ranges up to 80 µV. The mu rhythm is observed in the central head area with eyes open or closed. It can be observed as an independent, unilateral or bilateral brainwave on either brain hemisphere. It may also appear as an intermittent or continuous EEG artefact. The mu rhythm is attenuated by imagined or real contralateral motor activity and it's usually unilateral or asymmetrical. Mu rhythm can be clearly observed by blocking contralateral arm movement [**37**].

2.3.3 Beta Rhythm

Beta rhythms occur at frequencies greater than 13 Hz. They are normally observed within the frequency range of 18 Hz-25 Hz with the voltage of less than 20 µV. Beta frequencies observed beyond 25 µV in amplitude are considered to be abnormal. The potent activators of beta rhythm include benzodiazepines, barbiturates and chloral hydrate. These activators are generalised as fast activity activators for amplitudes greater than 50 µV and for greater 50% waking tracing within the bandwidth of 14 Hz-16 Hz. Beta activity usually increases during light sleep or drowsiness with mental activation. Reduced voltages greater than 50% which are persistent in activation suggests that there is cortical grey matter abnormality within the hemisphere thereby having lower amplitude. The lesser asymmetries characterising the rhythm may simply be reflecting normal skull asymmetries. Breach beta rhythm width may be produced with the presence of skull defect having focal, asymmetrically higher amplitude. This beta activity may occur without the skull to attenuate the frequencies [**37**].

Beta activity can be considered to be normal unless it is associated with spikes or focal slowing. Beta rhythms appear in the anterior head region and may be blocked by eye movement, muscle artefact emanating from the frontal lobes. Beta rhythm can be generally grouped into frontal beta rhythm, central beta rhythm, posterior beta rhythm and diffuse beta rhythm. The frontal beta rhythm is very fast and has no relationship to physiological rhythm. Central beta rhythm usually forms the basis of rolandic mu rhythm and regularly diversified with mu rhythm. The posterior beta rhythm is an equivalent of fast alpha rhythm and also reactive like the alpha rhythm. Diffuse beta rhythm has no relationship with any special physiological rhythm [**37**].

2.3.4 Theta Rhythm

Theta rhythms are observed at the frequency range of 4 Hz to 7 Hz and having varying amplitude and morphologies. Normal adults who are awake can exhibit intermittent 6 Hz to 7 Hz theta rhythms greater than 15µV. The intermittent theta rhythm is maximally observed in the frontal or fronto-central head regions. Emotions, focused concentration and mental tasks facilitate the appearance of frontal theta. Enhancement of theta activity is achieved through hyperventilation, sleep and drowsiness [**37**].

2.3.5 Lambda Waves

Lambda waves are surface positive sharply contoured theta waves that appear bilaterally in the occipital region. Lambda potentials occur within the time limit of 160 to 250 milliseconds. Lambda waves may sometimes be sharply contoured, asymmetrical have higher amplitudes than the resting posterior dominant rhythm. When lambda waves appear asymmetrical, they may be confused with interictal epileptic-form discharges and this may lead to the misinterpretation of the EEG signal. Lambda waves are best activated when an individual looks at complex pictures or scans textured images with fast saccadic eye movements. Placing white sheet of paper in front of an individual erases the visual input that is necessary for the genesis of lambda waves. Lambda wave amplitude is usually below 20 µV and may represent evoked response to visual stimuli [**37**].

2.3.6 Delta Rhythm

Delta rhythms are observed at frequencies less than 4 Hz of brain activity and comprises of less than 10% of the normal waking EEG by the age of 10 years. In the waking states, delta rhythms are found in the very young and elderly people. The normal elderly delta waves may have irregular delta complexes in the temporal regions of the brain. This activity is similar to temporal theta distributions, often found at the left greater than right temporal head regions. They are only present for less than 1% of the EEG recording. Excessive generalisation of delta rhythm is considered to be abnormal and shows an encephalopathy[8] that is etiologically[9] nonspecific. The structural lesion involving brain white matter of the ipsilateral hemisphere indicates the focal arrhythmic delta waves especially during continuous and un-reactive activity [**37**].

[8] Brain disease
[9] Having non-specific cause of delta rhythms

2.4 EEG Activity Types

EEG activity types are the modes of EEG and brain activity activation, EEG recording processes, potential generation and detection. Brain activities are usually detected using non-invasive brain imaging and EEG measuring techniques. Invasive brain activity detection can also be detected. Various non-invasive methods provide the necessary EEG data required for analysis. Sensor array on the scalp detect fields created by large neuron ensemble firing synchronously. These neuronal firings are approximated as current sources describing the spatial distribution of EEG signal. Current dipoles as observed by EEG sensor array provide the necessary estimation on dipole orientation, their number, location and frequency domain. Critical to the study of brain activity was the inverse problem. The inverse problem provides the mathematical relationship between source orientation and location. The inverse problem was efficiently solved by disregarding low amplitude EEG data. The inverse problem was divided into linear and nonlinear problem by using directed and global search algorithm based on pre-computed and large initial guess errors [**38**]. Source localisation algorithm improves the detection of brain activity [**39**]. Bayesian inference also provided an efficient technique in brain activity detection. Bayesian inference estimates the foci of active brain regions given that evoked potentials are used as the trigger. Bayesian inference detects brain activity without averaging the detected EEG data. The functional connectivity of EEG signal to the action intended in the neural circuitry is confounded by signal correlations and noise. This was an addition to the complexity associated in the analysis of brain activity, [**40**]. The integration of high resolution brain activity data with the local brain field expresses the functional connectivity existing between brain activity mapping and EEG signal source [**41**].

2.4.1 Spontaneous Activity

Spontaneous activity records EEG signal in response to some stimuli. The stimuli may be sound or visual. The EEG recorded usually contains some activity that has no direct relationship with the stimuli. Spontaneous activity is observed during and in between simulations and the results may be unrelated to the actual experiment that is being carried out.

2.4.2 Evoked Activity

Evoked Potentials (EP) are phase-locked at the beginning of the stimuli. This implies that each time the stimuli are applied; the potentials appear at the same latency with the stimuli. Most sensory stimulations generate evoked potentials. The amplitude of evoked potential was usually smaller than spontaneous activity and the evoked potentials are rarely visible in single EEG recording. By averaging the number of evoked potential recordings activated by the same stimulus, other activities are eliminated as the evoked potentials are phase-locked with stimulus. In general the signal-to-noise ratio (SNR) of evoked potentials is improved with the square root of the number of epochs[10] averaged.

2.5 The Brain Structure

The human brain structure has distinct features that separate human beings from animals. The brain at different occasions has been referred to as the super computer. The brain can process data simultaneously. The brain is basically a mass of fatty tissue with numerous neurons inter-wired with each other. The full capabilities of the human brain has not yet been realised as the brain is the most complex known living structure in the universe. The activities of the brain include the control of all activities that is perceivable by the human body and system. The complex control mechanism of the brain is what makes and defines us human beings. The brain's cerebral cortex is divided into four sections namely: the temporal lobe, the occipital lobe, frontal lobe and the parietal lobe. Some of the sections are associated with more than one function. The forebrain is where the highest intellectual activity happens. Intellectual activities include: planning, thinking, and problem solving. The hippocampus is associated with memory. The thalamus functions as the transmission station for almost all of the information coming into the brain. The neurons found in the hypothalamus function as transmission stations for the internal regulatory system. They function by monitoring data coming in from the nervous system and control the human body through the nerves and pituitary gland. The midbrain is made up of the colliculi. The colliculi is the collection of cells that transmit specific sensory information from sense organs to the brain. The hindbrain is made up of the pons, the medulla oblongata and the cerebellum. The medulla oblongata assists in the control of the respiratory and heart rhythms. The cerebellum assists in the controls of movement and cognitive processes requiring precise timing [**42**].

2.5.1 The Neuron

The neuron is the dedicated cell designed to transmit data from one nerve cell, to another nerve cell, gland cells or muscle tissues. The neuron is the primary working unit of the brain. The complexity of the brain is only what it is as the result of its structure, function, characteristics and the interconnectivity of the neurons. The neuron is made up of the cell body containing the nucleus, axon[11] and cytoplasm. The ends of the axons finish off into smaller branches before ending at nerve terminals. The neurons communicate with each other through specialised contact point known as synapses. The dendrites extend from the neuron cell body in the tree-like structure and are used to receive information from

[10] Epoch is the complete representation of brainwave data in finite training data set
[11] Axon is an electrically excitable output fibre.

other neurons. The dendrites and the cell body are enclosed by synapses form by the ends of axons from other neurons [**42**]. The parts of the brain are shown in figure 2-1 [**42**].

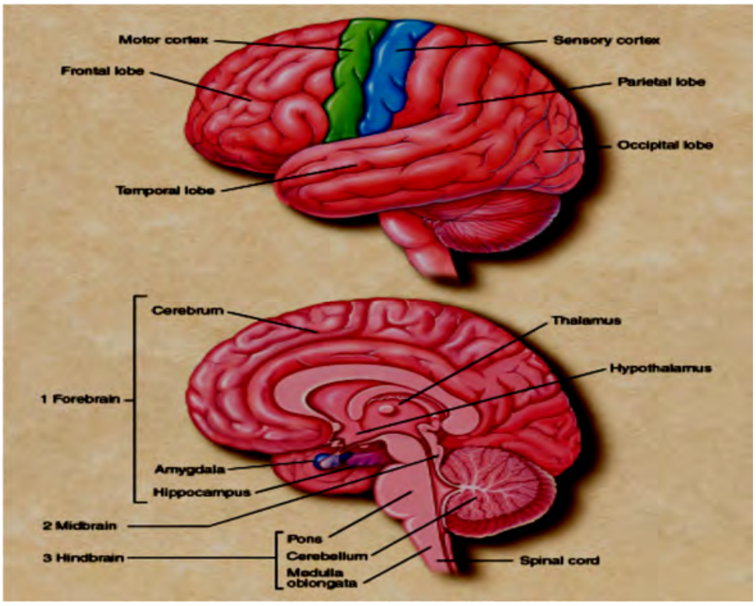


Figure 2-1: The Parts of the Brain

Neural axons range from fraction of an inch to three or more feet. Neurons communicate with each other by transmitting electrical impulses along these axons. The axon, a major transmission line within the neural structure is covered with layer of insulating sheath made from dedicated cells known as oligoden-drocytes. The structure of the neuron is shown in figure 2-2 [**42**]. Oligoden-drocytes are found in the brain. The axons found in the peripheral nervous system are also covered with insulating sheath made from Schwann cells. The function of the insulating sheath is to facilitate the transmission of electrical signals along the axon at the high speeds without interference. Nerve impulses are generated by the opening and closing of ion channels[12] in the cell body. The active flow of ions in and out the neuron creates electric current that generates small voltage changes across the neural membrane.

The neuron is said to fire when it has been sufficiently activated by incoming synapses to discharge and communicate to its own synaptic target neurons. The ability of the neuron to fire depends on a minute difference in electrical charge between the outside and the inside of the neural cell. At the inception of the nerve impulse, a striking reversal occurs at one point on the cell's membrane. The change is known as action potential. This potential is passed along the membrane of the axon at an extremely high speed. This process allows the neuron to fire impulses as many times as possible in every second. The numerous impulses fired by the neuron generate varying voltages upon reaching the end of the axon and triggers the release of neurotransmitters[13] at the terminal end of the nerves. The neurotransmitters

[12] Ion channels are water-filled molecular tunnels that pass through cell membrane and allow ions or small molecules to leave or enter the cell
[13] Neurotransmitters are the brain's chemical messengers

diffuse across the intra-synaptic space and bind to the receptors on the surface of the target neuron. The receptors function as on and off switch for the next neural cell. Each of the receptors has distinctively shaped part that recognises specific chemical messengers. Once the transmitters are in place, the outer membrane potential of the neuron is altered and this triggers a change in the cell [**42**].

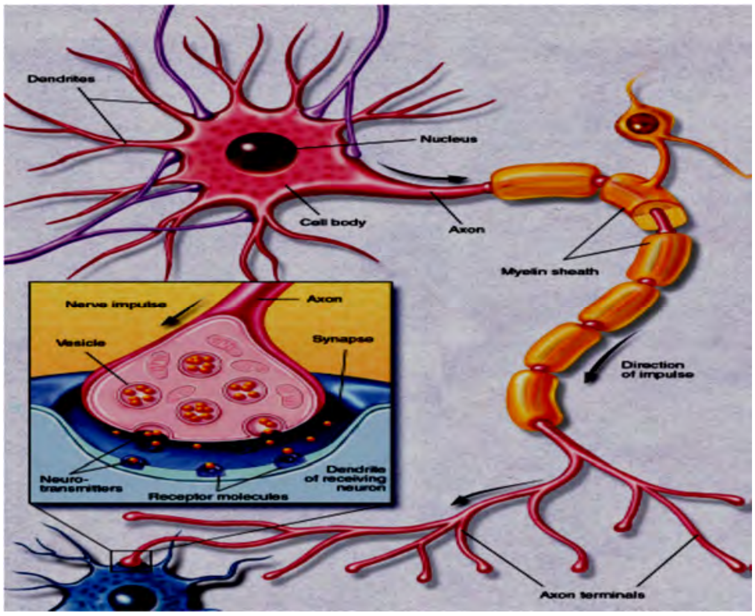


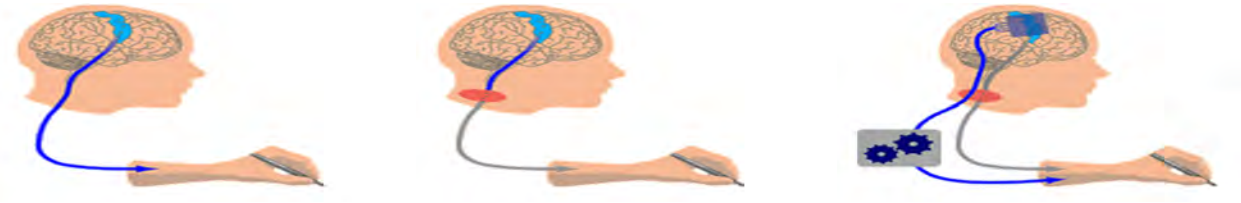
Figure 2-2: The Structure of the Neuron

2.6 Advances in BCI Technology

The progress made within the scientific community has demonstrated that in theory, that it is possible to drive prostheses, control computers and electronic devices using brain activity. The focus of the various researches around the globe in this new communication technology has been rooted into two different prototypes. These prototypes are the Invasive brain-computer interfaces and the non-invasive brain-computer interfaces. Human mental activity is usually accompanied with excitation and inhibition of distributed neural networks. Probable mental activities include intention to move or pick up something, decision making and metal arithmetic and calculations. Adequate sensors allows for possible recording of the changes in electrical potentials and magnetic fields with metabolic origins and sources. Subsequently, the development of BCI may be based primarily on the signal processing of electrical potentials, metabolic recordings, haemodynamic[14] recordings and magnetic fields generated by the human anatomy. The primary motive underlying the development of BCI is shown in figure 2-3 [**43**]. The successful deployment and utilisation of BCI system requires an extensive and energy intensive training of the users. The users are required to go through several training sessions to enable them gain

[14] It is the process used to identify the dynamic regulation of blood flow to and in the brain and forms the bases for functional magnetic resonance imaging (fMRI) [**192**]

control of their brainwaves. The users need to learn how to maximise the characterisation and classification accuracy of the different brainwaves and cognitive states. The user first trains with predefined mental tasks at the initial stage at regular intervals. By doing these repetitive tasks, the computer learns to identify and recognise the user's mental task related brainwaves.



The brain articulates movement commands and transmits them to the muscles through the spinal cord in healthy individuals

Physically challenged individuals have bridged communication pathway due to spinal cord injury

A new communication pathway is being proposed. Electrodes measure EEG from the brain. BCI system decodes and translates the EEG signal into control commands for semi-autonomous control.

Figure 2-3: The General Motive Underlying BCI Development

The learning process is highly dependent on the type of activity that is of interest to user and it is subject specific. For each user, there has to be a separate training session. The use of visual feedback has an important effect on the dynamics of brain wave oscillations. This can facilitate or deteriorate the learning process [**44**]. The ability of humans to move or control robots by sheer thought was an attribute of life form that was shown in science fiction screen plays. The concern of transforming this concept into science reality has become more and more prevalent in recent researches. Recent scientific view of reality does not involve any form of mystic or telepathic power. Scientists are working toward the development of systems that can effectively harness the brain electrical activity of human beings.

These activities are represented by small voltages measured at consecutive points in time with the aid of computer systems. Since such computer systems in one way or another tries to convert the thoughts of human beings into machine readable format, is called the Brain-Computer Interface (BCI). The BCI occasionally known as direct neural interface (DNI) or brain machine interface (BMI) provides direct communication conduit between external electronic device and the human brain. The brain's cerebral electric activities are recorded by means of EEG electrodes attached to scalp as shown in figure 2-4 [**45**]. These EEG electrodes measure the cumulative average electric signal of the human brain. The signals are augmented and transmitted to the computer which then transforms the signals into command signals for controlling electronic devices. The brain's electrical activities are the reflection of motor intentions and are detected by the BCI. The concept of using BCI brings together huge variety of disciplines. The disciplines include mechanical engineering, computer science, and electrical engineering, electronic engineering, physics, biology, mathematics and many other disciplines as the need arises. The huge variety of technical know-how makes it difficult to keep up with research and on-going comprehensive studies in using BCI for human development.

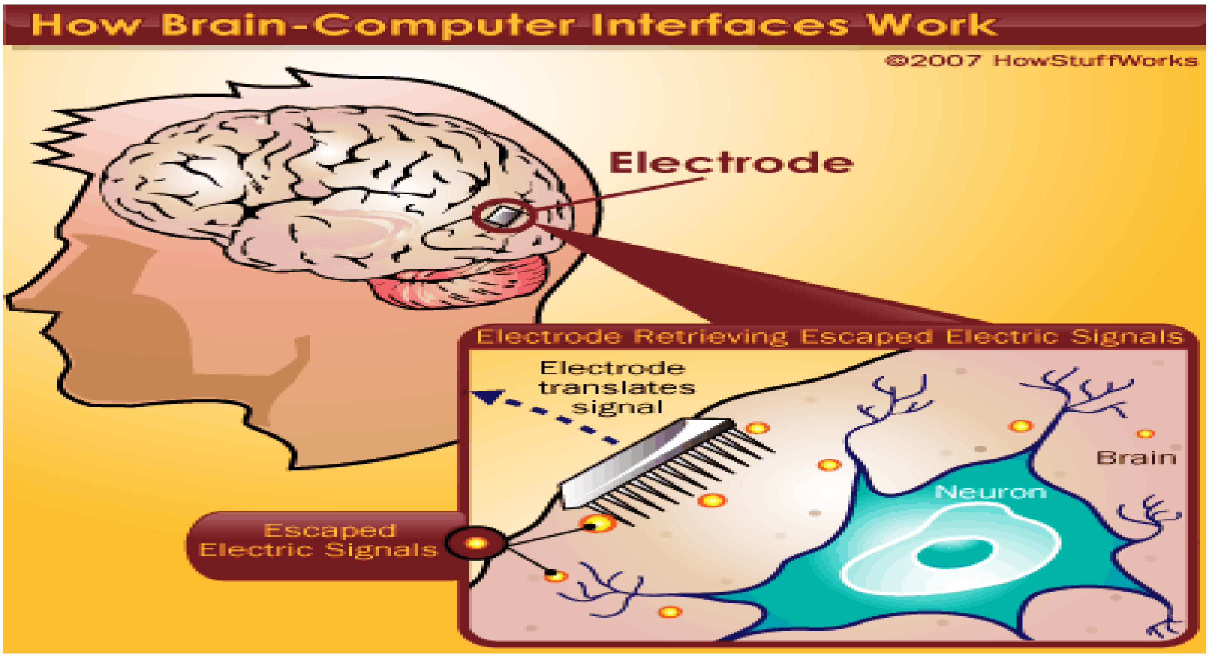


Figure 2-4: The BCI Electrode

In order to make the study as universal as possible the following questions were considered from various perspectives. These were:

- What kind of knowledge do we have about EEG?
- What are EEG signals used for and how can its application in robotic hand development be expanded?
- Why and how can EEG be used in improving BCI system?
- How can computer systems make sense out of EEG signals?
- What are the possible applications of EEG?
- Of what importance is EEG to mechatronic and robotic systems?
- What is the quality and accuracy of existing BCI systems?

The purpose of the BCI was to facilitate the communication of its user with computer systems by sheer thoughts of human beings. The objective of the BCI was to develop harmonious and intelligent environment between human beings and machines. The development of the cordial relationship between human beings and machines facilitates more natural and convenient communication protocol. This facilitates improvements in the quality level of people associated with high level information systems [**46**]. There are notable reasons in using a new way of communication with robotic systems as opposed to traditional input methods using the mouse and keyboard. Mind-controlled robots require almost no physical effort from the part of the user. It requires no muscle contraction and the requirement for the user is just to have a clear mind. This is very advantageous to individuals with severe disabilities. Disabled persons may not talk, move their feet, legs, arms or hands as they have almost no motor control in their brain architecture. Physical disability in this study refers to an individual who has no mental problems and has an active mind that is locked in an immobile body [**29**]. This development makes it possible for the physically handicapped to use and operate the BCI system. This can be their only avenue to make a difference and influence their environment positively. The coordination and control of robots in any environment using human thoughts brings into play the full characteristics of the BCI system. The BCI system detects and translates neural signals into control commands and control sequences for computers and robots. The recordings from EEG electrodes attached to the brain allows for transmission of information to the computer to facilitate the mechanical movements of robots. The BCI system was aimed at rehabilitation and restoration of human motor control in patients having multiple sclerosis, spinal cord injury and stroke. The performance of this system is aimed at integrating human subjects into societal functionalities [**47**].

2.6.1 Early Researches on BCI Technology

The researches into the functioning and brain behaviour monitoring have been going for the past six decades. The thoughtful comprehension of some brain behaviour characteristics has given many research institutions the opportunity to record brain signals. The brain signals were recorded from the cerebral cortex of animals such as rats and monkeys [**48**]. The primary objective of the recorded signals was to operate brain-computer interfaces. In these researches, monkeys were found to be capable of navigating computer cursors on the screen. The moving of a robotic arm by using their cognitive intelligence and thinking about the activity without any motor output were also attempted [**49**]. Researches are been conducted to develop algorithms that are capable of reconstructing movements that were initially generated by the motor cortex neurons. Neuroscientists have established that monkeys can control the firing rate of individual neurons in the motor cortex through voluntarily in closed loop BCI setup. The rapid improvements in BCI technology facilitated the capture of sophisticated brain motor signals from groups of neurons for the control of external electronic devices [**50**]. Initial intra-cortical brain-computer interface was designed and developed through the implantation of neurotrophicone electrodes into monkeys. The electrode placement process targets brain cells in the thalamus lateral geniculate nucleus [**51**].

These brain cells were basically responsible for decoding signals from the eye retina. Neural groups are thought to be responsible for the reduction in the variability of a single electrode output. These may introduce difficulties in the operation of a brain computer interface. Initial researches on rats in the 90s paved the way for the development of brain computer interfaces that could decode brain activity in monkeys. These brain activities were used to reproduce monkey movements in robotics arms. Research has shown that monkeys can be trained to use brain-computer interface to track visual targets on the computer screen using a closed-loop brain-computer interface [**51**]. Three-dimensional tracking brain computer interface was developed for tracking in virtual reality and also in the control of robotic arm. The recordings from pre-movement activities generated from the brain's posterior parietal cortex have been implemented in brain computer interfaces in the past as well as experimental recordings from animals in occasions when the animals were excited. The advancements in BCI technology have allowed for the prediction of electromyographic signals and the prediction of kinematic and kinetics of legs and hands movements. The advantage and importance of this progress is that it could be used and implemented in rehabilitation of paralysed limbs. This could be implemented through the electrical stimulation of muscles so as to restore the mobility capability of such individuals [**52**].

2.7 Overview of EEG-Based BCI Systems

An overview and review of the current EEG-based BCI systems is presented in this section. Each BCI system reviewed has its unique function and capability.

2.7.1 Wadsworth BCI

The Wadsworth Centre brain-computer interface system was developed in the eighties initially running at 9 Hz for cursor control in normal adults. The system was based on the cue system and autoregressive characteristics. The system used the linear function to define cursor movements which were necessary for character selection. In recent times, the Wadsworth BCI system has been enhanced to provide communication and control functionality to individuals who have no muscle control [**53**].

2.7.2 The Tuebingen BCI

The Tuebingen BCI was developed to assist patients who were completely paralysed by amyotrophic lateral sclerosis to regain their communication skills with the help of information acquired from their brainwaves. The system comprised of self-regulated slow cortical potential shift measurement device. The device made measurements in the space of two seconds operating on the cue-based system for ball-like movements [**54**]. After several training sessions, patients suffering from paralysis were able to write readable texts [**55**] using the Tuebingen BCI technology. The Tuebingen BCI system is a multi-task system with an adequate feedback system [**56**]

2.7.3 The GRAZ BCI System

The Graz BCI system was developed to increase communication possibilities and to assist individuals with chronic neuromuscular disabilities. The Graz BCI system is a cue-based system with motor imagery as its primary strategy and classification of brain wave activity within 10-20Hz frequency band [**57**] The parameters used in the system are adaptive autoregressive parameters and the band power of the brain waves. [**58**].

2.7.4 The Donchin's BCI System

The Donchin's BCI system was developed by Donchin and Farwell in 1988 and it was based on a 6 x 6 matrix system. The BCI system presented the user with a matrix of 6 x 6 cells, each having a letter of the alphabet. At short intervals, the rows or the columns of the matrix cells are flashed. The user intensifies his attention on the cell containing the letter to be communicated at an oddball sequence. This was implemented on the P300 BCI machine and the communication rate of about 7 characters per minute at 80% accuracy was achieved on the P300 system [**59**].

2.8 CNV and ERP

This subsection discusses the two important areas of research in the field of cognitive robotics and BCI technology development. The two areas of research which were investigated are event-related potentials (ERPs) and contingent negative variation (CNV). The section considered the processes involved in ERP and CNV generation. The system efficiency through the measurement of electrical activity of the human brain as measured from electrodes placed on the scalp was also considered. It discusses the use of cognition in robotics in developing the BCI system and BCI technology applications.

2.8.1 ERP Generation

It is well accepted that ERP activities originates within the brain. Brain activities and daily EEG observations are not been completely in harmony in relation to physiological determination of artefacts and psychological determination of ERP waveforms. The net representations of the electrical fields present at the scalp are captured using ERP recordings. These recordings are associated with sizable neural activities at the scalp. Individual neurons have certain geometric configurations and are synchronously active with each other. This allows them to generate electrical fields that are measurable at the scalp. Neurons are configured such that their individual fields in total produce dipolar fields. Open fields [15] are formed from the parallel alignment of neurons. From neurophysiological and biophysical considerations [**60**], scalp-recorded ERP waveforms are the consequence of post-synaptic[16] potential reflections rather than potentials from axonal actions.

The interpretation of the neural processes detected in the ERP has important consequence to the field of robotics. It was without doubt that there are neural activities that are detected elsewhere on the human body. Open field configuration of the neurons in these areas reveals that there is no sufficient synchronous activity to generate electrical field in the area of interest. The total selective process of the ERP is both advantageous and disadvantageous. The observation of the total brain activity at the scalp

[15] The dipolar neural fields with both positive and negative charges between which current flows are known as open fields

[16] Synaptic referring to dendritic potentials

and the resultant measures that are introduced produces complex analysis process. At the same time numerous important neural processes cannot be detected using ERP method.

2.8.2 Concerns in ERP Recording

ERP was obtained through recording the difference in voltage between two EEG electrode areas. The extraction of time-locked EEG epochs and the calculation of an average over the epochs revealed the ERPs. The concern that was raised in the use of EEG electrodes was the location of suitable sites for EEG signal recordings. Common reference recording procedure was used during EEG recordings. This reduced the ambiguities that were associated with the location of suitable sites on the brain. The common reference procedure required that each member of the EEG electrodes be connected to a single reference comprising either an electrode or pair of electrodes linked together. The electrode reference site was chosen in order to be relatively uninfluenced by electrical activity of the EEG recordings. The 10-20 reference system was used to describe the sites for EEG electrode placements. With the 10-20 system, electrode sites were specified in terms of its proximity to particular brain regions. The brain regions included the frontal lobe, central lobe, temporal, parietal and occipital lobes. The subscript *z* was used to describe the brain midline, odd numbers signify left of the brain and even numbers signify right of the brain. These are illustrated in figure. 2-5. Figure 2-5[17] provided useful stamp for the indication of electrode placements during routine recording [**61**].

2.8.3 ERP Wave Forms

ERP waveforms were represented as the grand average of EEG waveforms. They were generated from averaging together the averaged individual waveform forms of an individual. The advantage of using the grand average representation was that it made the variability representations of the waveform to hide the similarities that were present. The disadvantage of the method was that grand average may not represent accurately the pattern of the human subject results [**62**].The variability that exists in ERP waveforms may be classified as within-subject variability and between-subject variability. The variability present in ERP waveforms may be attributed to a variety of factors. The factors range from global factors such as the number of hours of sleep the previous night, body temperature to shift in task strategy. The striking observation made in the use of grand average waveform was that the peaks of the waveforms were smaller than single-subject waveform peak. The time it took to reach the peak value for an individual was not equivalent with the time it took for other test subjects. Single subject voltage peaks also differed with the peaks in grand average. Research findings on test subjects indicated that there are numerous positive voltage time points in some of the test subjects. The voltage time points

[17] The outer circle of the figure is drawn at the level of nasion and inion. The inner circle represents the temporal line for the EEG electrodes [**110**].

may be negative in some of the test subjects. The grand average voltage peak was smaller than the individual voltage peaks [**62**].

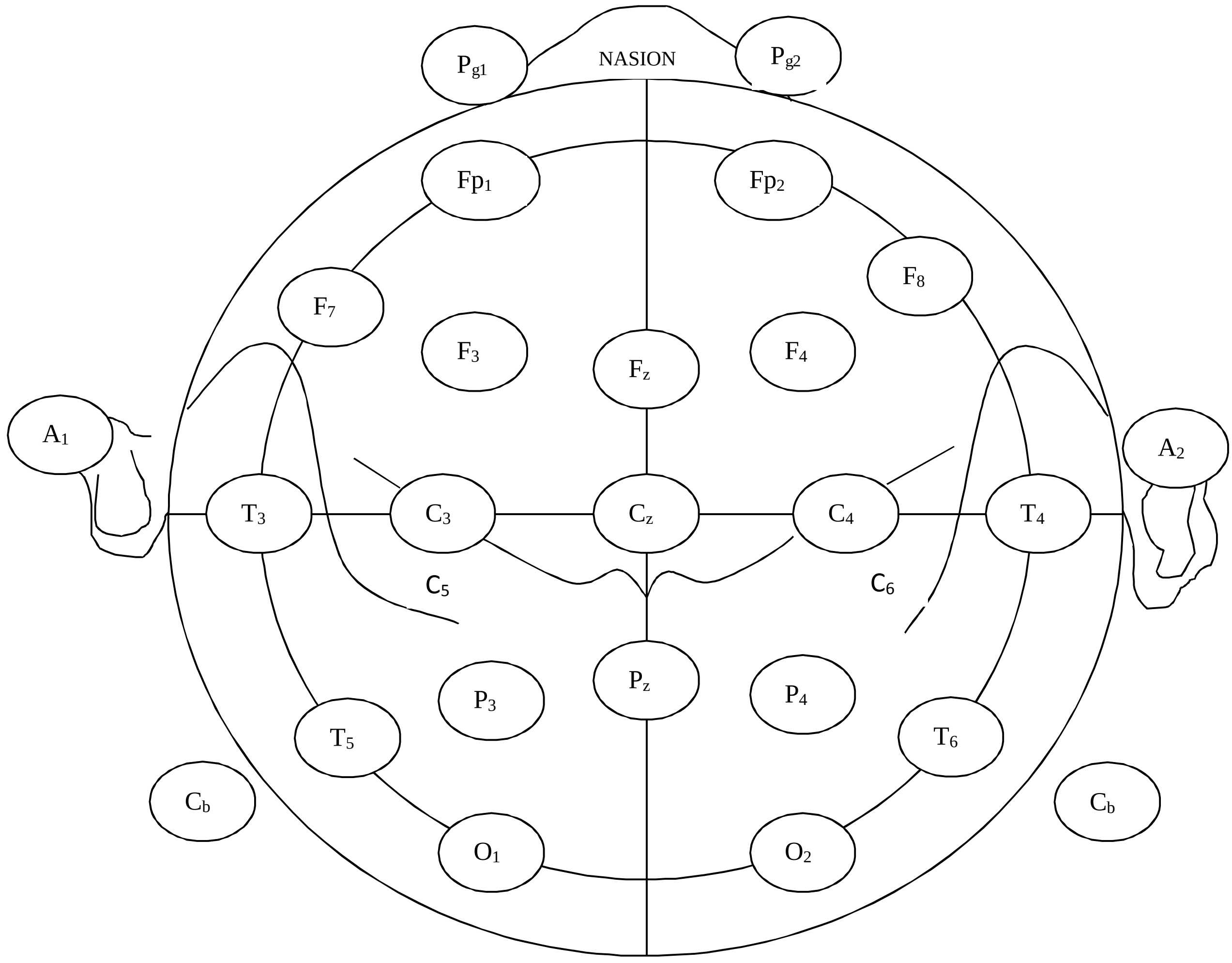


Figure 2-5: The 10-20 EEG Electrode Placements. The Single Plane Projection on the Scalp Shows Standard Positions and Locations of the Brain Rolandic and Sylvian Fissures.

The waveform of ERPs generated as the result of response from cognitive activity was made up of signal peaks and deflections characterised by ERP components. The ERP components include latency, morphology, topography and experimental manipulation [**63**]. The ERP components had small signal amplitude with the range of 1 to 20μV. The Signal-to Noise Ratio (SNR) of the ERP components were improved as the function of the square root of number of EEG epochs ($1/\sqrt{N}$). The division of ERP amplitude by the standard deviation of the pre-stimulus interval provided suitable method for measuring the SNR for the particular ERP component of interest. The pre-stimulus interval formed the basis for estimation of zero potential. Alternatively, the SNR can be computed by using the difference of ERPs centred on even and odd-numbered epochs. The division of the difference in ERP waveform by two indicated the phenomenon known as the plus-or-minus reference. This gave an indication of the noise estimate in the ERP. It was less dependent on the assumption made in the generation of the ERPs [**63**].

2.8.4 The Pros and Cons of ERP Technique

Cognitive neuroscience and behavioural measures in robotics have introduced the ERP techniques which are useful in measuring the speed and accuracy of motor responses. Motor responses in bio-signal patterns have discrete stimuli and responses. This forms the crucial fundamental reference in the measurement of ERP signals. The distinct advantage of the ERP technique was in the measure of processes that existed between the stimulus and the response. These measures evaluated and compared the behavioural measures that generated signals for robotic control. Open responses reflected the output from large number of individual cognitive processes and their variation in association to reaction time. The accuracies of responses were difficult to correlate to variations in specific cognitive process. The ERP technique in contrast provided continuous measure of processes that occurred between the stimulus and the response. This made it possible to ascertain which of the processes are affected by external stimulus. ERP technique can provide signals for the coordination and control of robots in the absence of behavioural responses from the human subject. This was the second distinct advantage of the ERP technique in generating signals for robotic control [**62**].

The disadvantage of using ERP recordings was noticed in the functional significance of the ERP component signal when compared to behavioural measures and response. The ERP functional component signal was not as clear as the functional significance of the behavioural response. This was because the sources of the ERP responses were uncorrelated and were not attributed to specific biophysical events. The consequences of these events in relation to information processing for robot command generation were also uncorrelated. The second disadvantage in the usage of ERP signals was that ERP the signals were very small and required several trials for accurate measurements to be taken. The long hours of trials in ERP measurements placed significant limitations on the types of questions that can be answered effectively using the technique. It was of paramount importance that ERP experiments and tests were aimed at questions and researches for which ERPs were noted for. This was because ERP technique has both significant advantages and disadvantages. For this reason, ERP technique was used to answer questions that are related to neurocognitive processes influenced by specific manipulation and stimulus.

2.8.5 ERP and Cognitive Robotics: The Conceptual Concerns

For many cognitive scientists involved with information processing, the objective of cognitive robotics was to identify cognitive processes that mediate between the environment and open behaviour. The representations, interactions of these processes and their temporal properties in the execution of simple robotic motion were of concern to cognitive scientists. The traditional techniques in the study of cognition do not permit cognitive processes and representations to be studied directly. Instead, cognitive observations are to be inferred by careful selection of experimental manipulations and the analysis of the effects of the manipulations on open behaviour [**61**]. Provided that cognitive processes are generated and implemented by the brain, the exploration and measurement of brain activities provided insights on the nature of brain signals. ERP was one of the many ways of measuring physiological activity in the central nervous system that can provide meaningful results in cognitive robotics. Related techniques include magnetic homologues of the ERP and EEG which involves magnetoencephalographic indices and parameters of spontaneous EEG.

2.8.6 Contingent Negative Variation (CNV)

The study of electrical activity in and within the brain has paved the way forward into research and better understanding of cerebral physiology. It has also provided insight on the ability to access human brain function efficiency as we know it. The Contingent Negative Variation (CNV) is the gradual negative shift in EEG recordings observed between the warning signal (S1) and an absolute stimulus[18] (S2) during a Reaction Time (RT) task. It is also regarded as the negative shift in EEG potential measured on the scalp in comparison to an electrical reference electrode placed on the earlobes [**64**]. Electric potential was measured as Average Electrode Potential (AEP) from the scalp. The CNV wave was attributed to human anticipation, expectation, intention to perform a task, attention, response readiness and orientation. The CNV wave has two components as shown in figure 2-6 [**64**]. The first component was the early wave CNV component that was associated with orientation response. The second component was the late CNV wave. It was associated with the test subject's readiness, potential to act and stimulus of anticipation [**65**]. The late CNV wave also indicated the level of motor preparation and stimulus anticipation. An interval of at least 4 seconds was required for Inter-Stimulus Interval (ISI) in order for the waves to be observed during trials [**66**]. The CNV paradigm was viewed in acceptance that the inter-stimulus interval and ERP took the shape of a specific negativity. CNV wave was an expectancy wave[19] [**67**]. The applications of CNV included its use in detecting brain disease as the dopaminergic biomarker [**66**], detection of Parkinson's disease, Huntington's disease, schizophrenia and other brain conditions [**64**]

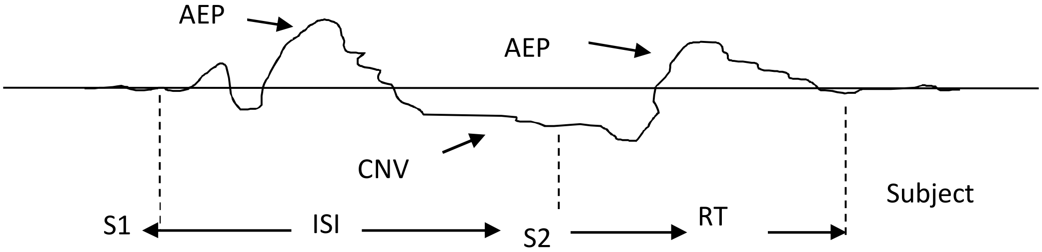


Figure 2-6: CNV Wave Schematic

[18] Also known as imperative stimulus
[19] Motor action preparation which is taken after S2. i.e. After condition S1, and event S2 is expected [**67**]

2.8.7 Progress in Invasive Brain-Computer Interfaces

The improvements made so far in the use of invasive BCI technology have proved to be useful in the repair and restoration of damaged eye sight and in providing new functionality to physically challenged individuals. Generally, invasive brain-computer interfaces are implanted directly onto the grey matter of the brain. As a result of the location and placement of the invasive BCI technology implants, they provide and produce the highest quality BCI technology signals. The down side in the usage of invasive BCI technology is that they are exposed to tissue damage and damaged tissue build-up which inherently causes the neuronal EEG signal to become weaker or lost in the event that the brain reacts to foreign objects appearing in its domain. Despite the difficulties associated in the implementation of invasive BCI technology, it has proven to be a success in the treatment of non-congenital blindness. The success of invasive BCI technology was usually evaluated in the area of motor neuro-prosthetics in providing rehabilitation measures and assisting in restoring movement in paralysed individuals or to control electronic devices [**68**].

2.8.8 Progress in Partially Invasive Brain-Computer Interfaces

Partially invasive BCI are BCI devices implanted inside the human skull. The remainder of the device stays outside the skull rather than being inside the brain grey matter. The search for better signals led to the development of partially invasive brain computer interfaces. They are able to detect and generate clearer signals than non-invasive brain-computer interfaces. The deficiency in using non-invasive brain computer interfaces was in the deflection and deformation of EEG signals by the bone tissue of the cranium. There was an advantage in the usage of partially invasive brain-computer interfaces. Partially invasive brain-computer interfaces had lower risk of forming scar-tissue in the brain [**69**]. Fully invasive brain computer interfaces may form scar-tissue in the brain. The development of light reactive imaging brain computer interfaces are in their early developmental stages and in recent times they are conceptual ideas. Light reactive imaging brain-computer interfaces are envisioned to facilitate the implantation of imaging lasers in the skull. ECoG techniques can be an adequate intermediate process in EEG signal acquisition as it has higher spatial resolution, wider frequency range, and enhanced signal-to-noise ratio. ECoG requires less training processes and time constraints than scalp-recorded EEG. In addition to the aforementioned advantages, it requires less technical know-how, has little technical complexity, lower clinical risk. It also has the higher chance of long-term stability than EEG recording from an intra-cortical single neuron. These characteristic advantages of ECoG have high level potential and minimal requirements for the development of BCI applications that are useful to individuals with motor disabilities [**70**].

2.8.9 Progress in Non-Invasive Brain-Computer Interfaces

Different trials have been conducted in human beings using non-invasive neuro-imaging technologies in the development of brain-computer interfaces. The signals acquired and recorded through this method have been useful in the restoration of partial movements and to power muscle implants. The downside of using non-invasive muscle implant activation mechanisms was that the signals generated had poor signal resolutions. The reason for this was that the scalp dampened the EEG signals and blurred the electromagnetic waves generated by the neurons. Electroencephalography has huge potential for developing non-invasive brain computer interfaces as it has fine temporal resolution, easily accessible and easy to use. The disadvantage in using electroencephalographic device was that it was prone to noise. It required extensive training for users before the system can be acclimatised to an individual's brainwaves. The use of fMRI and MEG has been successful in brain-computer interface trials. The advancements made have been able to use fMRI recordings of haemodynamic responses to control robotic arm. This was achieved with an approximate delay of measurable seconds between human thought and the execution of movement [**70**].

2.9 Emotiv and Neurosky Headsets

Emotiv and Neurosky are the EEG headsets that were used in the EEG signal identification, extraction and classification as presented in the thesis. The Emotiv headset has 14 electrodes that were placed on the scalp. It uses wet electrode technology in measuring EEG signal. Neurosky headset has a single EEG electrode placed at the forehead. Neurosky headset made use of dry electrode technology. Further discussions on Emotiv and Neurosky headset is presented in chapter 4 subsection 4.5.5.

2.10 The Robotic Hand

The robotic hand developed by the Mechatronic and Robotics Research Group was designed to assist a disabled person in Durban South Africa. The robotic hand components were designed using Autodesk Inventor professional and made using a 3-D printer. The palm and fingers were controlled using geared DC motors and rotated accurately using servo motors.

2.11 Summary

The chapter reviewed factors that influence and control the generation and transmission of EEG signals from the brain for use in robotic and mechatronic applications. The demonstrations that electrical activity exist in the brain have shown that these activities are generated through the ensemble of cortical neuronal activity. These can be employed directly to control mechatronic and robotic devices. Researches on BCI have experienced significant improvements such that neuronal signals are used for both clinical and experimental purposes. The studies were conducted with aim of translating the neuronal signals into motor commands. The motor commands replicate arm reaching and hand grasping movements in artificial manipulators. The BCI systems do have few bottle necks which can be resolved if these motion commands are to be effectively implemented. The bottlenecks include the design of fully implantable biocompatible recording device, the introduction of techniques that can provide the brain with sensory feedbacks from actuators, developing efficient real-time computational algorithms and building robotic devices that can be controlled directly by brain-derived signals.

The crucial important application of BCI technology was in the enablement of disabled and healthy subjects. BCI enabled them to operate electronic devices and computers directly using their brain activity as the primary input channel. BCI system provided the framework where the user can relay messages and commands directly from the brain without using the brain's normal communication pathways. The core intent for this new information pathway change was to control devices through neural activities. The bioelectric signal was encoded in the recorded EEG signals. Through EEG recordings, the BCI system can provide the brain with the new non-muscular communication pathway. The user can use and implement the new communication pathway in different applications as the need arises. The various applications include supporting biofeedback training in individuals suffering from epilepsy, stroke, control of robot arms, computer games and also to assist individuals with severe motor disabilities.

CHAPTER THREE

Brainwave Decoding/Coding Via IAF-ASDM in Adaptive EEG Neural Network Model

The chapter discussed the contributions made in brainwave data decoding and encoding in adaptive EEG neural network. In this chapter, the decoding and encoding of EEG signals in preparation for EEG artefact and feature extraction is presented. Adaptive predictive linear models were used in establishing the relationship between the predicted EEG signal and raw EEG signal. Adaptive neural philosophy provided the framework used in the development of the adaptive EEG neural network. Parametric modelling of EEG data and the spectral analysis of EEG data are also discussed in the chapter.

3.1 Introduction

The representation of biological neuron by mathematical function incorporated the biophysical and geometrical characteristics of the neuron in varying conditions. This defined the human brain adaptive neural modelling [**71**]. The mathematical model of the human neuron formed the basis for the biophysical parameter estimation and the neuronal computational properties development. Modelling the neurons in the brain required that complex phenomenon existing in brain activities are replaced by model entities. The operational properties and characteristics of the model entities as defined by recommended rules represented the behaviour of the human neural phenomenon. It was worthy to note that the empirical or simulated descriptions of brain activity were not by themselves logically coherent but provided the basis in which logical conclusion were reached. The primary objective of neural modelling was to describe the brain activity in terms of models that were inherently coherent. The behaviour of EEG signal can be predicted based on the presented models. In order to achieve the objective of active EEG signal prediction, the interaction between EEG measurements and the mathematical models were quantified by numerical analysis [**71**].

3.1.1 Chapter Motivation

The work presented in chapter 3 was conducted in order to develop an efficient EEG signal decoding and encoding system using an adaptive neural network system for use in the development of the robotic hand. The IAF and the ASDM techniques were employed in the development of EEG decoding and encoding system as they were complementary in their functional efficiencies. The IAF and ASDM performance also provided data on the computational lifespan of the decoding and encoding process which led to selection of appropriate microcontroller.

3.2 EEG Signal Processing Model

EEG signal quantity was referred to as any bio-signal resulting from discrete brain activity varying with time or any other independent cognitive variable. EEG signal processing provided the fundamental platform for EEG artefact identification. Biological signal analysis was deemed necessary in order to extract information from brain activity [**72**]. EEG signal represented the brain activity variations through which cognitive information was conveyed. EEG signal was used to express the state, characteristics, composure and course of actions of human beings. EEG signal provided the means by which human beings convey information regarding intents and actions. These intents and actions can be used for communication, control, decision-making, low level and high level human-machine interactions [**73**]. In developing BCI systems for robotic control, it was necessary to develop adequate system identification techniques for EEG signals for use in BCI systems. The BCI communication system generally comprised of EEG signal source $I(t)$, information mapping system and information transformation system into signal variation system $T[\cdot]$, the communication channel $h[\cdot]$, additive noise channel $n(t)$ and the EEG signal extraction system as illustrated in figure 3-1.

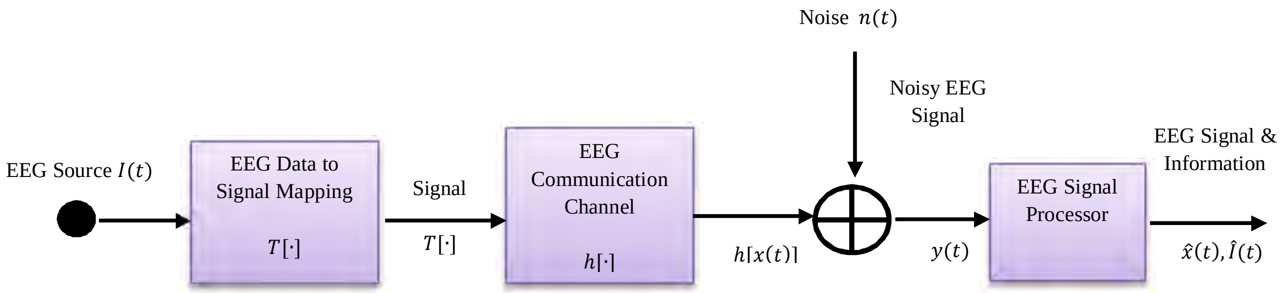


Figure 3-1: EEG Communication and Signal Processing System Model

The EEG signal processing architecture was aimed at developing efficient and robust EEG coding system, transmission, extraction and representable EEG information and communication system. Furthermore, the EEG signal processing architecture was also aimed at the extraction of valuable information from noisy EEG signal. These broad objectives allowed for the standardisation of EEG signal patterns, EEG signal detection, prediction, signal-enhancement and clean-up strategies for robotic control and automation. Biological signal processing techniques have advanced in algorithmic complexity with the aim of optimal implementation and utilization of encoded information. The techniques of interest in analysing EEG signals include the use of Bayesian statistical signal processing models, model based techniques, transform based analysis/ synthesis and neural networks [**73**].

Brain activity generated random electric signal which can be fitted in within the class of random signals in the multidimensional signal space. Brain activity can be described using statistical averages and modelled by probabilistic distribution function. Relatively, the combinations of numerous neural networks within the human brain are combinations of nonlinear adaptive signal processing subunits structured for information passage. Improvement made in analysing EEG signal sought to reduce the level of noise and interference caused by the other brain-wave generation activities. The use of adaptive noise cancellation classification provided an important application strategy in EEG signal processing.

3.3 Adaptive Brainwave Linear Predictive Modelling

Human cognitive activities include controlled and uncontrolled action. These activities generated brainwaves. Adaptive linear predictive models provided an efficient tool used for EEG signal enhancement for robotic control. The random brainwaves were spectrally shaped and coded. The effects of neural activity in the brain allowed for the introduction of correlation measures and predictions of random variations of brainwaves. EEG signal sources in the brain emitted random brainwave excitations which were filtered and modelled to reflect the different EEG signal frequencies. The brainwaves were modelled by the adaptive linear predictor in forecasting the EEG signal amplitude at time $m, x(m)$, with the linear combination of P previous brainwave samples $[x(m-1), \dots, x(m-P)]$. This is presented as [**73**]:

$$\hat{x}(m) = \sum_{k=1}^{P} a_k\, x(m-k) \tag{3-1}$$

where $\hat{x}(m)$ represents the predicted brainwave, the vector $a^T[a_1, \dots, a_P]$ represents the coefficient vector for the predictor in the order of P. The difference between raw EEG signal $x(m)$ and the predicted EEG signal $\hat{x}(m)$ yields the error vector and is presented as:

$$e(m) = x(m) - \hat{x}(m) \tag{3-2}$$

3.4 Brainwave Decoding and Implementation

Human neural networks are composed of large complex systems interacting through complex array of communication pathways. Neurons in the brain exhibit active conductance in large scale through wide variety of dynamic human behaviours. The complex system in which neuronal networks use in firing signals requires quite considerable amount of time to understand. The main concerns raised and addressed in modelling neuronal networks include [**74**]:

- How do we classify the large population of neuronal signal and accurately interpret their activities?
- How can neuronal networks be modelled as each neuron in itself is a complex system?
- How can neuronal networks be modelled with limited information on synaptic connections and communication patterns?

In order to address the aforementioned issues, the following four general strategic philosophies and techniques were applied in analysing EEG complex neural systems. The complex human neural network was analysed with aim of decoding of brainwaves.

- The functional and behavioural significance of human neural networks was considered to be critical in communication and information dissemination. This condition was adopted when neuronal patterns of brain activity can be accurately interpreted. Interpreting neuronal activity involved two step processes. The first step required the consideration of the individual neural spike trains then followed by the collective interpretation of the entire population of neurons. The second step analysed neuronal spike trains and the dynamics used for communication. The firing rates of neurons were the yard stick for characterising neuronal spike trains. Firing rates generated from linear filters provided an accurate description of the signal output from a single neuron. The output signal from a single neuron contained information that may be used in decoding neuronal signals individually or as the population of neurons. This provided the reflection on the neuronal activity and the interpretation thereof.
- The data carried in an ensemble of neurons provided the capacity to decode functional neuronal activity without losing the functional information contained in the neural activity. The effect of the properties of neuronal activity and synaptic characteristics of neural signal on large neural networks was usually complex and subtle. These effects when applied to the coded neural signal provided means of interpreting the signal. The decoding of neural signals using optimal linear filters coupled with efficient techniques of decoding neural populations provided means of extracting maximum data from neural circuit [**75**]. Decoding neural signal was the tool for analysing neural activity and to understand the complex nature of neural networks. The techniques used by the human nervous system in decoding patterns of neural firing do not necessarily correlate with the techniques used in decoding neuronal firings. It was assumed that the results generated from the neuronal decoding process provided adequate information and representation of the biological neural network [**76**].
- Synaptic signal strength changed during the course of neuronal activity and was determined through Long-Term Potentiation (LTP) and depression [**77**]. The effects of synaptic changes studied from LTP data provided rules which were implemented in computing synaptic strengths that may arise from specific training sessions [**78**]. The study on synaptic effects allowed for the examination of the impact of training sessions and network learning and adaptation. Provided that the synaptic changes are small, the impacts of synaptic changes in neural signal decoding were determined through linear computation of the neural signal. In the event where the synaptic changes are large, their effects became ambiguous and linear approximations were used as guideline for neural decoding [**74**].

- Providing adequate description and decoding neuronal activity was only one area of challenge that was crucial in the modelling of the neural network. Developing the neural network model that has the capacity to incorporate neuronal activity and how it changed with time was another challenge that was faced in the development of neural network that described EEG activity. In several cases, attempts were made to use the firing rates of neurons to build dynamic neural model that was purely based on the firing rates of neurons [**79**]. The activation and deactivation of large number of ion channels, the concentration of calcium and various messenger and communication molecules inside brain cells affect the firing rates of neurons in the brain [**80**]. The activities of these communication molecules cannot be effectively described with just only the firing rates of neurons. The firing rate model does not have to use first principles based on ion channels and other fundamental neuronal characteristics and properties to determine the firing rates of neurons [**81**]. Instead, the use of robust mathematical model of measured rates was implemented into the firing rate models in principle. This was augmented with various approximations for unmeasured components of the model. The dynamics describing the change in the firing rates of neurons was simplified to a large extent. The integration time used in defining the firing rate was made longer than the intrinsic neuronal time affecting the actual firing of the neurons to achieve simplification. Measured and computed static properties of neural firing rates was used in developing the dynamic firing rate model which allowed the inclusion of nonlinear effects in the model [**74**].

3.5 Adaptive Brainwave Digital Decoding/Coding

Adaptive biological signal processing in neural networks for various signal analysis applications have significantly advanced especially in EEG signal analysis. The progress made in analysing EEG signals and their prospective applications in BCI, BMI, mechatronics and robotics was attributed to efficient signal processing techniques. Two key methods were important in encoding EEG signals in neural networks. Integrate-And-Fire (IAF) and the Asynchronous Sigma-Delta Modulator (ASDM) are the two important techniques used for the process of encoding/decoding of EEG signals. Neural networks have the ability to learn from their operational environment under supervised and unsupervised learning conditions. The linear and nonlinear characteristics of EEG signals were masked into the neural network as they shared the same characteristics. Neural network generally uses mathematical computing techniques to mimic biological neural systems [**82**]. The neural network as modelled by McCulloch and Pitts in their work [**83**] is presented as [**82**]:

$$u = \sum_{j=1}^{N} w_j y_j + \theta \tag{3-3}$$

where $y_j; 1 \leq j \leq N$ represents the networks inputs, $w_j; 1 \leq j \leq N$represents the synaptic weights and θ represents the network bias or threshold. The neural output k was related to the neural input u

through activation functions which may be linear or nonlinear in their transformation functions while taking into consideration the effects of temperature T on the neural network performance. The neural network may be activated using various activation functions which are listed in table A-1 [**82**] in appendix section. The various activation functions are used to encode or decode analog EEG signal using either IAF or ASDM technique. The bandwidth required to transmit brainwaves in real-time and EEG Signal-to-Quantisation Ratio (SQR) were directly proportional to the bit per signal sample. The aim of the EEG signal coder was to achieve high EEG signal reliability with few bits per sample as much as possible. The EEG signal coding process utilised statistical characteristics of the signal and the EEG signal generation model together with information on human cognitive behaviours. The brainwave coder can either be model-based coder or transform-based coder. Figure 3-2 and figure 3-3 illustrates the steps implemented in coding and decoding brainwaves using model-based techniques.

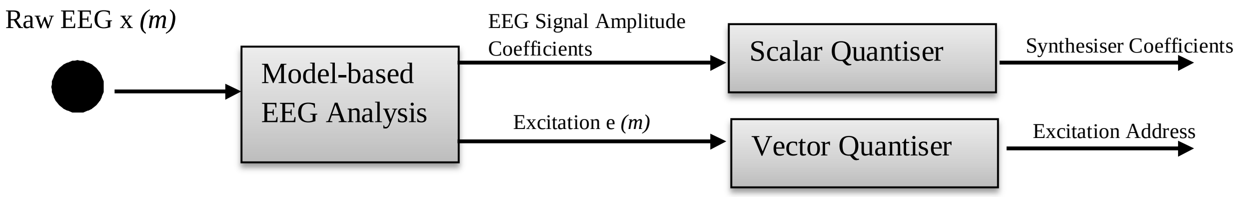


Figure 3-2: Brainwave Coder Schematics

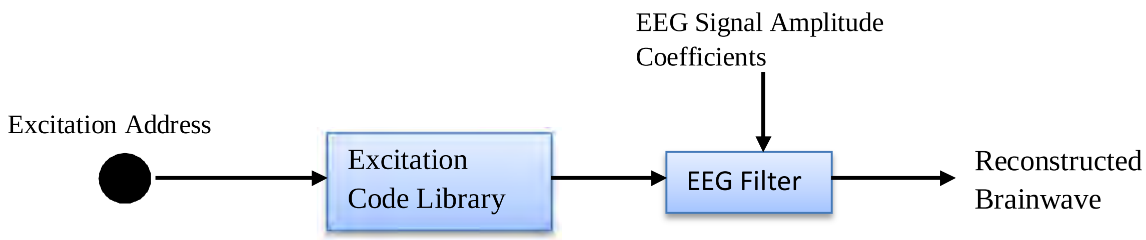


Figure 3-3: Brainwave Decoder Schematics

The transform-based coder transformed the EEG signal into frequency domain using discrete cosine transform or filter bank or Fourier transform. This allowed the signal to be manipulated with ease. It also provided convenient and useful interpretation for controlling electronic devices. Coding brainwaves in frequency domain rendered the following advantages:

- EEG signal frequency spectrums were well defined.
- Low-amplitude frequencies were masked close to high-amplitude frequencies and were coded without any significant signal degradation.
- The EEG frequency samples were orthogonal and were coded independently with different accuracies.

The number of bits assigned to each brainwave was the reflection of the contribution made by that specific brainwave in the reproduction of clean brainwave. With an adaptive coder, the allocation of bits to different brainwave frequencies varied with the signal power spectrum time variations [**73**]. Figure 3-4 [**73**] illustrates the coding of brainwaves using transform -based coder.

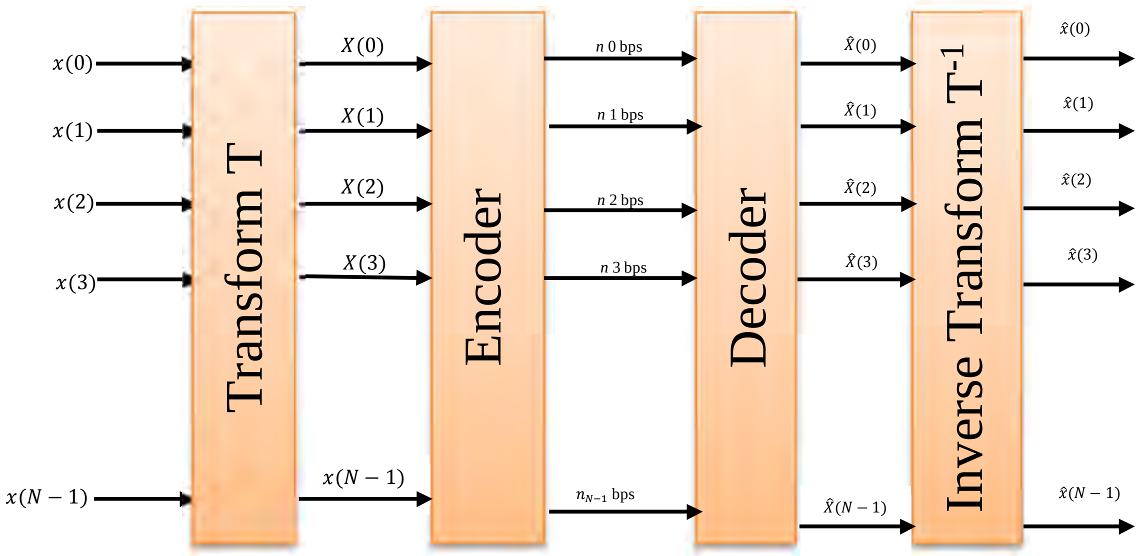


Figure 3-4: Transform-Based Coder/Decoder System

3.5.1 EEG Signal Noise Modelling

In observing and recording EEG signal, noise $y(m)$ present in the signal was modelled as:

$$y(m) = b(m)x(m) + n(m) \qquad (3\text{-}4)$$

where $x(m)$represents the observed EEG signal, $n(m)$ represents the noise in the observed EEG signal and $b(m)$ represents the binary-valued state indicator sequence. $b(m) = 1$ indicates the presence of observed EEG and $b(m) = 0$ indicates that the observed signal was absent. The corresponding EEG filter for detecting EEG signal and impulse response $h(m)$ of the corresponding EEG filter represents the time-reversed version of the observed EEG signal $x(m)$.

$$h(m) = x(N-1-m) \quad for\ \ 0 \le m \le N-1 \qquad (3\text{-}5)$$

where N represents the length of the observed EEG signal. The output of the corresponding filter is presented as:

$$z(m) = \sum_{m=0}^{N-1} h(m-k)y(m) \qquad (3\text{-}6)$$

The coordinated filter output $\hat{b}(m)$ was compared with the stipulated threshold and the binary decision was made according to equation (3-6).

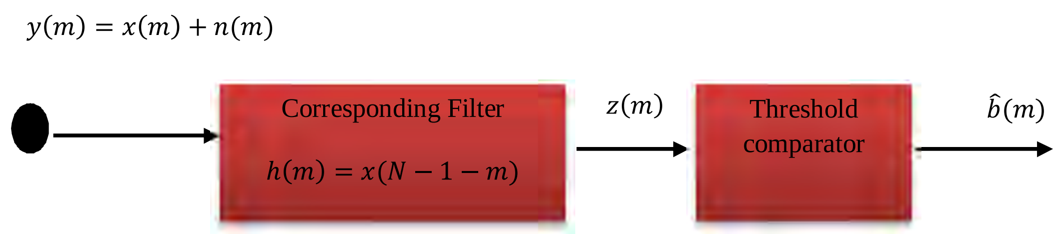


Figure 3-5: Corresponding EEG Filter Configuration for Noise Detection

$$\hat{b}(m) = \begin{cases} 1 & if \;\; z(m) \geq Threshold \\ 0 & otherwise \end{cases} \tag{3-7}$$

The threshold decomposition provided an efficient technique in EEG analysis and binary filters [**84**].

3.6 The Brain Neural System

The human neural system has the advantage of sending selective signals across the human neural network and can easily adapt to complex and changing environments. An adaptive artificial neural system modelled in accordance to the human neural system provided a suitable platform having the adaptability to accept inputs and outputs. These input and output units were instrumental in communication with the immediate environment. The input and output units are connected by uni-directional connections. Each connection was characterised by the weight and the sign that transforms the signal into readable signal to the hidden or internal units of the neural network. The artificial neural system as modelled by McCulloch-Pitts [**85**] has similar signal transmission characteristics as the biological neural system. The artificial neural system represented in figure 3-6 [**86**] has the output signal y_i and presented in equation (3-8) and equation (3-9) [**83**]

$$Sum \;=\; \sum_{i=1}^{N} I_i W_i, \tag{3-8}$$

$$y = f(Sum) \tag{3-9}$$

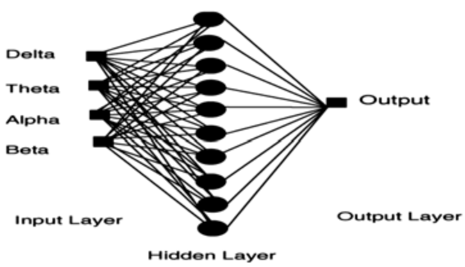


Figure 3-6: BCI ANN Architecture

where I_i represents neural sets of inputs, W_i represents weighted normalized values for each of the inputs within the range of either (0, 1) or (-1, 1). The function f represents the linear step function modelled at the threshold T shown in figure 3-7 and Sum represents the weighted sum of the output y.

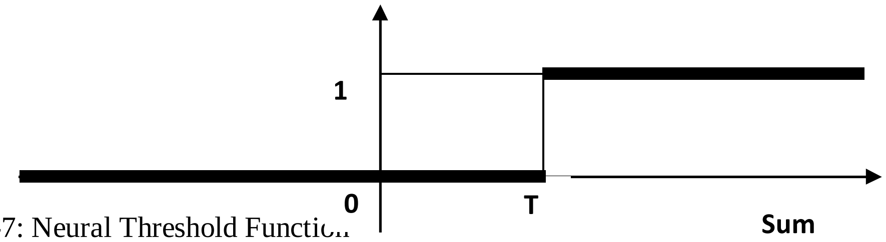


Figure 3-7: Neural Threshold Function

3.6.1 EEG Spectral Analysis Structure

Neurophysiological analysis of the cognitive processes underlying the performance of a human being controlling a robot through human thoughts was an essential area of this research. The study presented useful conclusions in determining the various data patterns and information processing analysed from EEG recordings in real-time. It also aimed at detecting accurate or inaccurate responses from real-time EEG recordings. In analysing EEG signals, common spectral patterns, the computation of the spectral power of EEG channel and cross channel power correlations were very crucial to the credibility of the prediction, artefact extraction and classification of EEG signals. The EEG spectral analysis followed three most essential processes and these are [**87**]:

- Data digitization and signal conditioning
- Band pass digital filtering
- Spatial power computation and pattern analysis

The overall structure is represented in figure 3-8.

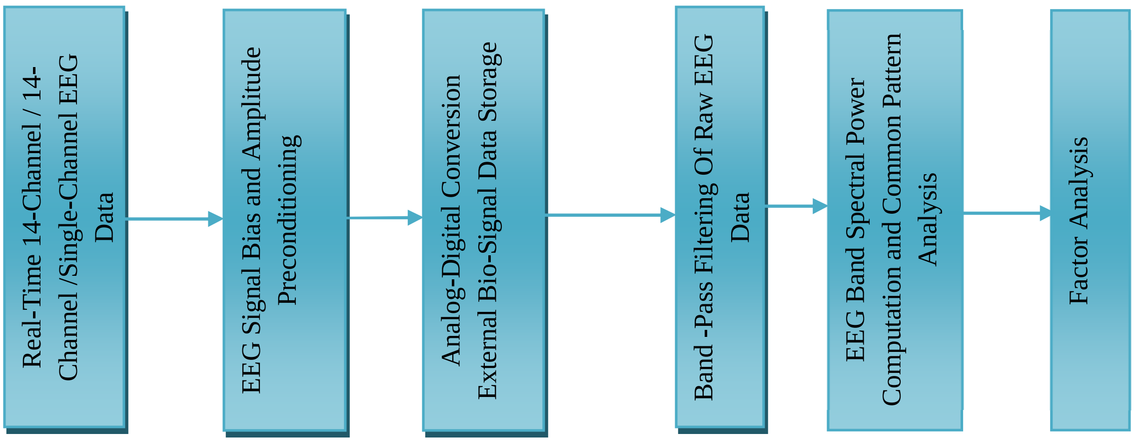


Figure 3-8: EEG Spectral Analysis Architecture

3.7 Parametric EEG Data Modelling

Analysis of EEG data using parametric modelling has long been established [**88**] [**89**]. Several models such as linear parametric model, Auto-Regressive Moving Average (ARMA) and Auto-Regressive Integrative Moving Average (ARIMA) were used to fit EEG data. These models provided explanations required for performing EEG time series analysis. The complexity and stability of EEG signal was discussed using the concept of signal stationarity in adaptive and non-adaptive parametric models [**89**]. The non-stationary characteristics of EEG signal and its change with time depended on active mental state at any given moment. In order to adequately represent EEG signal, it was assumed that over short time intervals, EEG signals were stationary. Batch processing algorithms were then applied to the signal to obtain optimal parameter estimate for each of short time intervals. The estimation of optimal EEG signals was implemented using Burg algorithm and the Levinson-Durbin algorithm [**90**].

3.7.1 Burg's Algorithm

In order to effectively analyse EEG recordings, the EEG data were segmented. Burg algorithm provided the framework for performing recursive estimate of the model coefficients from continuous multiple segmented data [**91**]. In the given set of N discrete EEG data, k coefficients were used to approximate the original values y_n in the forward linear prediction process and z_n in the backward linear prediction process. In appendix E, the detailed discussion on the derivation of the parameter estimate μ for segmented continuous EEG data is presented.

3.7.2 Levinson-Durbin Algorithm

Parameters for segmenting random EEG signal were estimated using the Levinson-Durbin algorithm. The Levinson-Durbin algorithm made use of autocorrelation techniques in linear parameter prediction [**92**]. In the given set of signal values $(y_n)_{n \in [0,M]}$ extending to $(y_n)_{n \in z}$ and having infinite number of zeroes, y_n were approximated using the best k coefficients $(a_n)_{n \epsilon [1,k]}$ by $- \sum_{i=1}^{k} a_i y_{n-i}$. Detailed discussion on the parameter estimate derivation for segmenting EEG data is presented in appendix F.

3.8 Results and Performance Investigations

This section presents the results and performance throughput of the EEG encoder-decoder model implemented in the study. The EEG data were segmented using Burg's algorithm and the signal parameters were estimated using the Levinson-Durbin algorithm. The transform based signal encoder/decoder algorithm was integrated with ASDM and IAF to increase the computational efficiency of encoding and decoding of EEG signal. In figure 3-9, the ASDM EEG signal encoding with sigmoid activation function result is shown and figure 3-10 shows IAF EEG signal encoding with sigmoid activation function. The EEG encoder and decoder viewed the EEG signals as analog signal. In figure 3-11, the original EEG signal is shown before being passed through the encoder and decoder process using ASDM technique. In figure 3-12 the result from the ASDM encoder is shown. In figure 3-13, the result from the ASDM decoder is shown. The red lines in figure 3-12 and figure 3-13 are the outputs from the ASDM encoder/decoder process. The blue lines in figure 3-12 and figure 3-13 are the initial EEG signal before encoding or decoding takes place. The errors measured in dB from each process is also shown figure 3-12 and figure 3-13 respectively and the number of neural spikes used in the process. Figure 3-14 shows investigations on the sensitivity of ASDM encoder which are influenced by the EEG signal bias factor, signal threshold and signal scaling factor. Figure 3-15 displays the result from fast ASDM EEG signal decoding process. Figure 3-16 displays the original EEG signal before passing through IAF encoding and decoding process. Figure 3-17 shows results from EEG signal encoded using IAF process. Figure 3-18 shows the results from the decoding of EEG signal using IAF process.

Figure 3-19 illustrates results from fast IAF EEG signal decoding. The red lines in figure 3-18 and figure 3-19 are the outputs of the IAF decoder and the blue lines are the original EEG signal. Figure 3-17 indicates that the IAF encoding and decoding process requires more neural spikes than the ASDM EEG signal encoding and decoding process. The IAF encoding and decoding process requires more computational processing power than the ASDM process especial considering its application in embedded systems for robotic control. The sequences of neuronal spikes in both the IAF and ASDM are indications of strong EEG signal. This implied that there was ample EEG data to be analysed in extracting the EEG artefact of interest. The performance of the encode-decoder system was validated in the ability of the system to capture the all information contained in the EEG analog signal. Different time coding was experienced when the starting time of the EEG analog signal was varied for the EEG signal input. Increasing the time bias factor decreased the performance of the encoder and decoder. The bias factor, signal scaling factor and threshold specifications were critical factors influencing the performance of the encoder and the decoder.

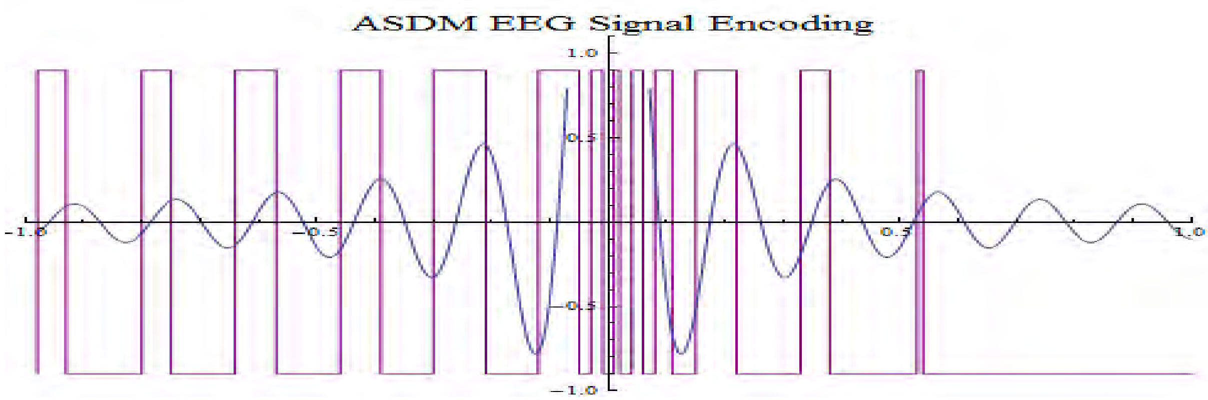


Figure 3-9: ASDM Encoding With Sigmoid Activation Function

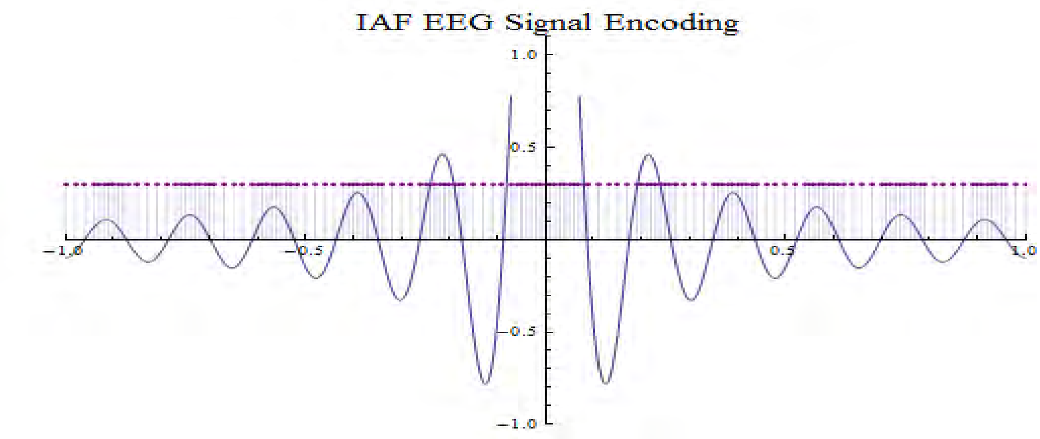


Figure 3-10: IAF Encoding With Sigmoid Activation Function

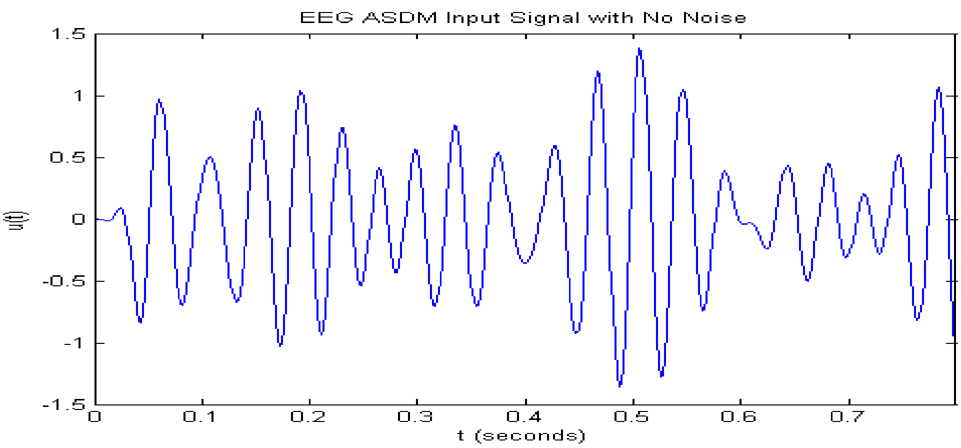


Figure 3-11: EEG signal input with no noise

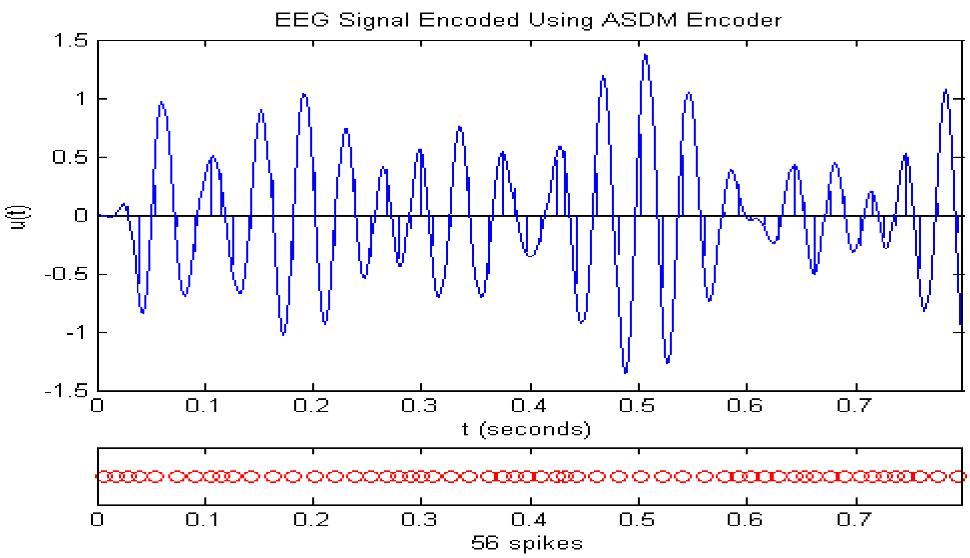


Figure 3-12: EEG Signal Encoding Using ASDM Encoder

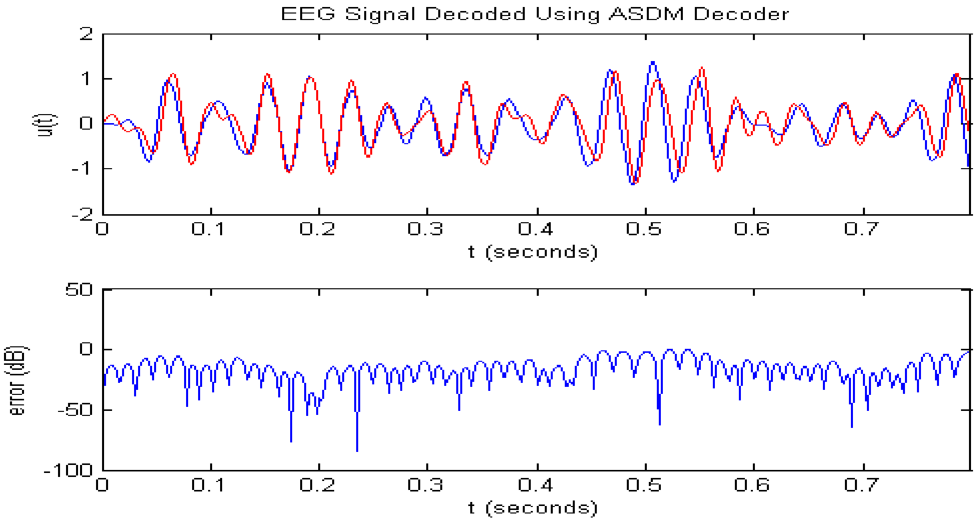


Figure: 3-13: EEG Signal Decoding Using ASDM Decoder

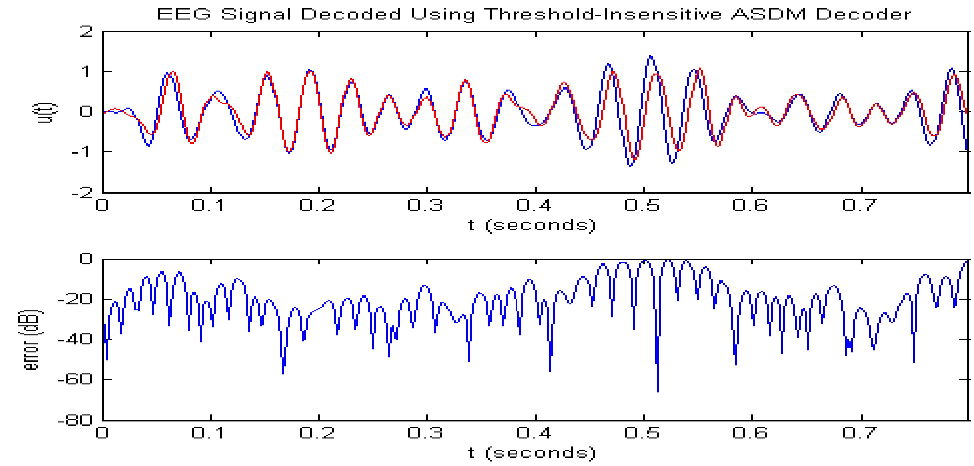


Figure 3-14: Threshold Insensitive EEG ASDM Decoder

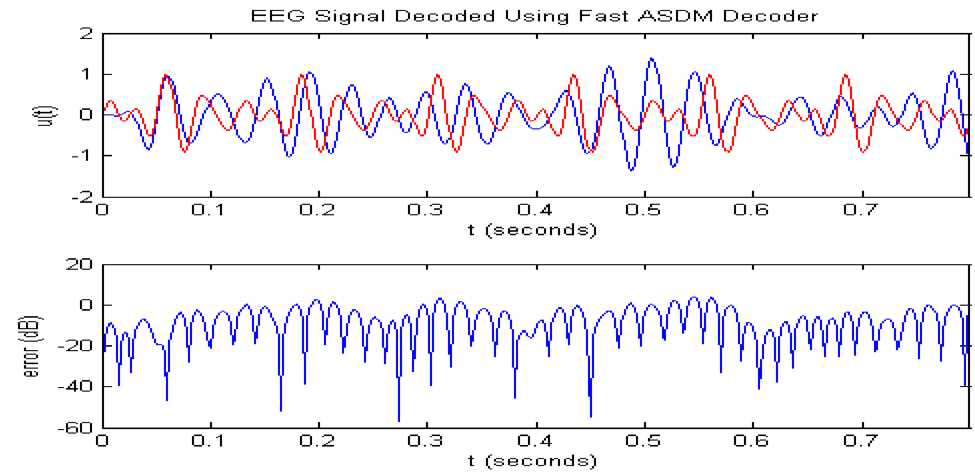


Figure 3-15: Fast EEG ASDM Decoder

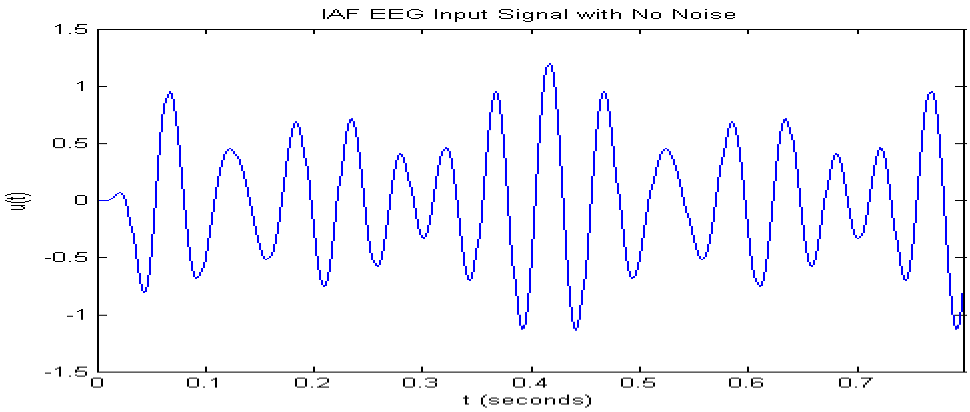


Figure 3-16: EEG Input Signal with No Noise

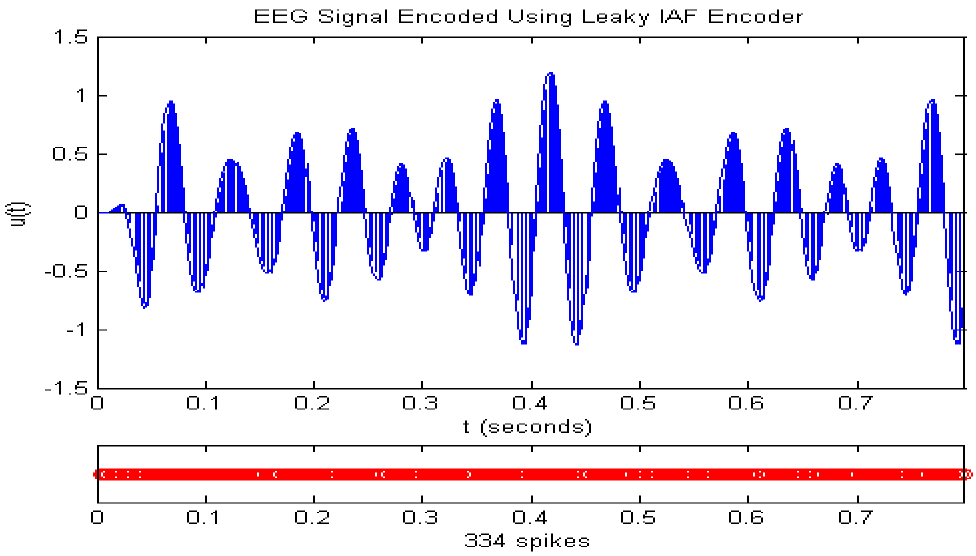


Figure 3-17: EEG Signal Encoded with IAF encoder

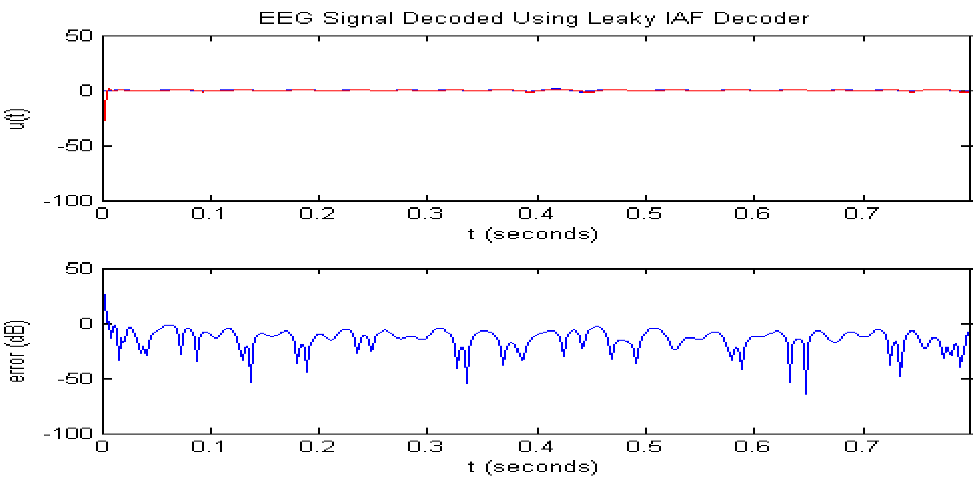


Figure 3-18: EEG Signal Decoded with IAF Decoder

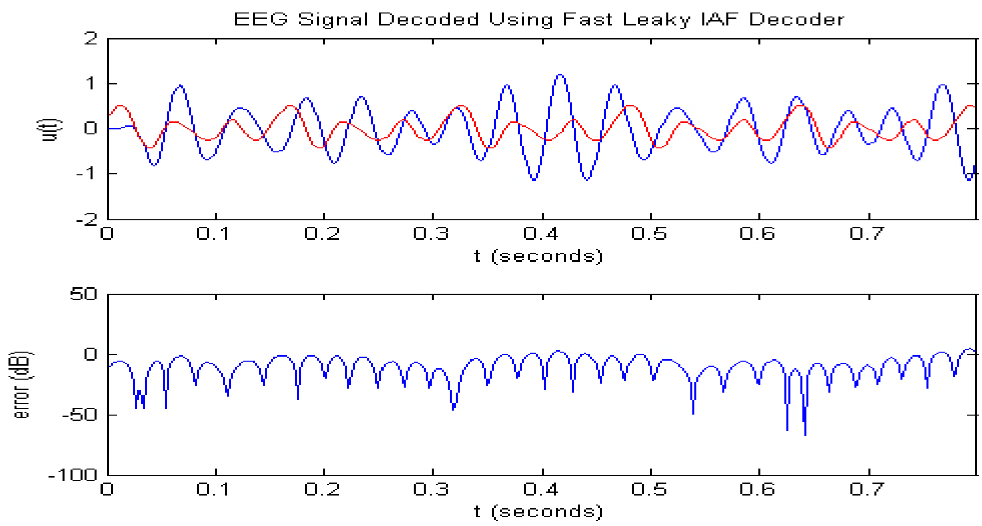


Figure 3-19: EEG Decoded Using Fast IAF Decoder

3.9 Summary

The encoding and decoding of EEG signals was employed at the deployment of human cognitive process for implementation at the adaptive EEG neural network. This was presented in the chapter. The identification and rejection process for extracting EEG signals suitable for robotic command control codes as the function of evoked potentials from the human brain required strategic processing of the signals in adaptive neural network. The strategic processing of the EEG signals were functions of the EEG signal encoding and decoding processes. The selection of evoked potential as excitation models from the brain was based on the local response signal conflict resolution of the test subject. Quantiser models were instrumental in establishing the relationship between EEG signal excitations and reconstructed EEG signal for use in robotic and mechatronic applications. The interaction rules between the neuronal layers provided the framework with which the Integrate-and-fire (IAF) and the asynchronous sigma-delta modulator (ASDM) models were implemented. Burg's and Levinson-Durbin algorithms were used in determining the segmented EEG signal coefficients in the adaptive neural network. The performance of the encoder and decoders were influenced by the bias function and the threshold limiters which are specified for different EEG signal recording conditions. The work in this chapter was performed in order to investigate and validate the performance of ASDM and IAF models in decoding EEG signal for the control of a robotic hand.

CHAPTER FOUR

Integrating Wireless Autonomic Neural Network with Action Observation Network in EEG Data Management

The chapter discussed the contribution made in the complex augmentation and integration of wireless autonomic neural network with action observation network. The wireless autonomic EEG network model and design is presented. The recording setup, electrode placement, EEG signal source estimation and brain modelling were crucial in developing the EEG data management system. EEG signal source estimation was used to showcase the importance of overlapping EEG spatial spectra. The results presented in the chapter are reflections of the experimental setups in evaluating the data management throughput of the autonomic neural network in the presence of action observation activities.

4.1 Introduction

Advancements made in wireless sensor networks were aimed at transmitting information effortlessly in widely distributed networks for robotic control. Wireless Sensor Network (WSN) applications in bio-signal transmission significantly facilitate EEG signal acquisition process. The EEG signal acquisition process using WSN optimized bio-signal conditioning and often reduced the care and cost of managing the signal acquisition process. EEG electrodes placed at the scalp, in the brain or on the skin constitute EEG wireless sensor networks. Each EEG electrode formed a network node for receiving and transmitting bio-signals. Due to the low cost and power consumption of the EEG technology, it opened possible application avenues for industrial process controls and robot navigation [**93**]. WSN specific performance features allow specific electronic devices to efficiently transmit and receive bio-signals [**94**]. Integration of microcontrollers, sensors and transmitter-receiver modules formed the basic architecture for the WSN. Energy consumption needs and processing capacity of the WSN provided insight into the efficiency of the WSN. Wireless sensor networks are classified according to the applications and functions of the sensing technology. Robot motion responsiveness determines the application of each classification. Wireless sensor network classes include:

Heterogeneous Network: This refers to WSN having different hardware at the nodes integrated together. It is referred to as a homogeneous network.

Autonomous Network: This refers to WSN node self- configurability without human intervention.

Hierarchical Network: EEG signal communication nodes are grouped together. Communication base station bridges external communication between human and robot.

The wireless sensor network has four subsystems. The subsystems are:

Computing Subsystem: Communication protocols and sensor controls were coordinated and implemented using the microcontroller. The power management processes allowed the microcontroller to be operated at different modes.

Communication Subsystem: Module operating frequencies and standard wireless signal transmission protocols may consist of either radio frequencies or Bluetooth protocols. Short range radio signals allowed for communication between the EEG headsets and the computer and other wireless network nodes. The communication modes included transmission, sleep and standby.

Sensing Subsystem: This included each electrode linked in the WSN with its power management system.

Energy Storage Subsystem: The energy supply of the EEG headset came from the rechargeable battery. WSN subsystems were designed such that the energy management of each component complements the efficiency of the signal transmission and process from the headset.

4.1.1 Chapter Motivation

The work presented in chapter 4 was performed in order to showcase the importance of autonomic wireless network in the transmission of EEG data. The action observation network was developed in order to transform cognitive processes into machine readable commands for use in controlling the robotic hand. The wireless autonomic network augmented with the action observation network was designed to automatically respond to EEG signals.

4.2 EEG Wireless Autonomic Network System

Autonomic network systems are systems which are capable of exhibiting self- managing characteristics and functions. Autonomic system provides self-management in the computational architecture of control systems. In this chapter, EEG information management and transmission system is presented as the high level computing system. The high level computing system was void of human effort in the running and operational maintenance of the network. The EEG autonomic network system provides robust data management and transmission application in the adaptive neural network presented in the previous chapter. Automatic subdivision for information management and transmission introduced in the EEG autonomic network system eliminated the need for human involvement in the running and keeping of the system. The development and design of the wireless autonomic network system was inspired from the functioning of the human nervous system. Considering that EEG data originates from the brain and forms part of the nervous system, it was worthy to develop and implement the wireless autonomic system with little or no human intervention. The EEG autonomous network utilized the principles of autonomic computing in managing the information transmission in the adaptive neural network [**95**]. The sole purpose for the EEG wireless autonomic system development was to have a wireless network that was self-adaptive, self-healing and self-managing. The design of the EEG wireless autonomic system presents high level complex distributed computational architecture shown in figure 4-1 for self-managed EEG information transmission. The applications of autonomic technologies in robotics and mechatronic systems were developed using five different information management and transmission processes. These include:

- **Basic Level:** In this system, the system operator managed information transmission from setup to decommissioning manually for entire life cycle of the robot or the mechatronic system.
- **Managed Level**: In this system, the system operator utilized the available information transmission and management technologies to monitor multiple information outputs simultaneously. This was done with adequate human machine interfaces or BCI.
- **Proactive Level**: Sensor information was utilized to provide analytical solutions leading to proactive decisions. Warning systems were used to propose solutions to the operator.
- **Adaptive Level:** In this level, the robotic or mechatronic system collected information from the environment and was able to predict and react autonomously without human assistance. The specification of actions in possible scenarios required situational judgment for lower level decision making and actions.
- **Autonomic Level:** In this system, it was expected that the interactions between the human nervous system and machines were constructed on high-level objectives and functions. The high-level information policies were encoded in the network architecture and the system responded according to the interpretations of the policies.

In developing the wireless autonomic network system, it was critical to identify the autonomic network computing characteristics. The associations in the autonomic network initiatives were identified with aim of fulfilling its objectives. The key objectives for the autonomic computing architecture are self-configuration, self-optimisation, self-healing and self-protection. In appendix A-1, the RN-171-XV wireless modules is shown. Two RN-171-XV and two X-bee Pro wireless modules were used in the implementation of the EEG wireless autonomic neural network system.

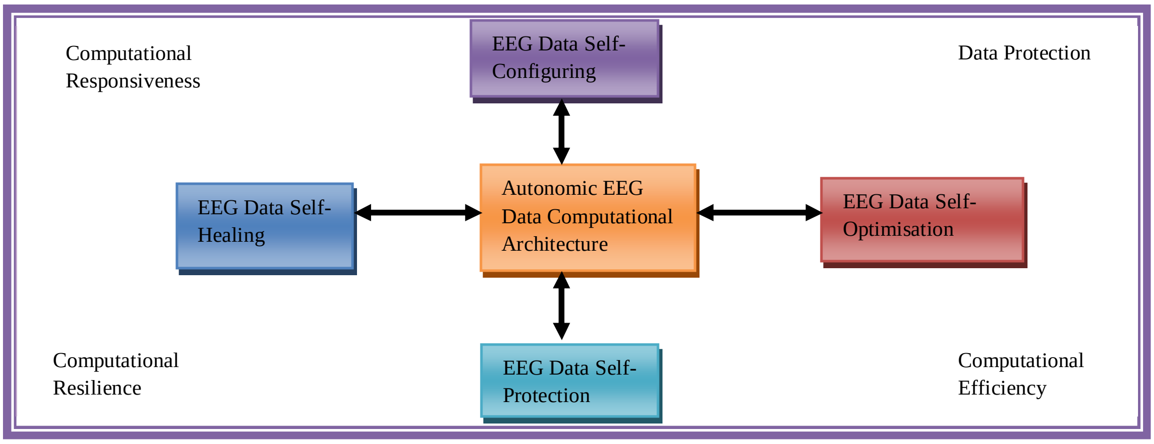


Figure 4-1: Autonomic EEG Data Computational Architecture

4.3 The EEG Autonomic Network Design Philosophies

The concepts and principles on which the EEG autonomic network was modelled were based on the mode of information exchange in the human nervous system. The properties exhibited by the human nervous system during information transmission were valuable in determining the survivability of the autonomic network. The mutual behaviour of the subsystems in the EEG autonomic network system was also instrumental in determining valuable network properties. These properties included:

Network Survivability: The EEG network internal mechanisms were continuously matched to generate essential network variables which were within the limits defined by the EEG data transmission thresholds. The adaptive functionality of the network subsystems were the key ingredients to the survivability of the EEG autonomic network. The system was designed such that the data transmission was within its capacity. When there were external stimuli requiring transmission of mega data, the system readapted and readjusted its working mechanisms in order to maintain the specified data transmission viability region. The adaptation mechanisms played important role in the survivability of the EEG neural network system.

Mutual Behaviour: The collective performance of the autonomic network subsystems influenced the overall performance of the EEG autonomic network system. Local information transmission challenges became the global determining factors influencing the network behaviour.

The EEG wireless autonomic neural network was modelled using four basic constructs. These constructs are the fundamental blocks of the wireless autonomic neural network system as it defined EEG data interactions, operations and transmission. The constructs formed the basic communication archetypes integrated in the wireless autonomic neural network. The four basic constructs are: the EEG data functional block, the wrapper, Data Dispatch Point (DDP) and data channel.

Data Functional Block: The EEG data functional block was responsible for processing and forwarding of EEG data across the autonomic network. This abstraction allowed for the integration of different communication protocols within the autonomic neural network.

The Wrapper: The wrapper encapsulated information of interest into formats that allowed the data to have unique network characteristics. This reduced conflicts of interest in EEG data management across the autonomic neural network.

Data Channel: With the wireless autonomic network data wrapper, the nature of information service was abstracted by the data channel. Data channel may have logical or physical characteristics. Data channel abstraction may include point to point wireless communication, mesh wireless network construct etc.

Data Dispatch Point: The data dispatch point in the wireless autonomic neural network provided the necessary access point for the data functional blocks. Interactions were carried out in the autonomic network through indirection level across the core autonomic network constructs.

In order to be at par with the rapid technological advancements in BCI technology development; the complex EEG data management system was developed with the aim of introducing self-computing, self-optimization and self-configuration. This allowed the EEG data management system to meet the high level demands of the autonomic neural network system. In this section, the autonomic neural network EEG data management system is presented. The EEG data management system was developed around autonomic neural network policies. This ensured that the autonomic behaviour of the EEG neural network was preserved. The autonomic neural network policies were expressed in terms of goal policies, behavioural policies and network utility function policies. Utility-based analysis was instrumental in developing the EEG distributed data management task force in providing common data model in the autonomic neural network. These abstractions denote the metrics required in computing the Quality of Experience (QoE) as observed in the subject and the implementation process. The QoE was instrumental in maximizing the user's satisfaction level and ensured that there was good return in investing in EEG headsets as semi-autonomous control tool [**96**].

In exploiting the usefulness of IP networks in transmitting and managing EEG data, there were real challenges which may be beyond the conventional network management principles [**97**]. There were complexities associated with managing bio-signal data, and the enablement of efficient network infrastructure capable of providing the desired reliability. This introduced new motivation in the search for new techniques in transmitting and managing EEG data. The self-management of EEG data in accordance to the principles of autonomic network architectures ensured that high-level objectives specified in the EEG neural network were met. The mid-level objective of the autonomic neural network data management system ensured that high-level neural network objectives were refined into low-level autonomic neural network policies. The decomposition of the policies required that various control coordination concepts were engraved in the neural policy descriptions and policy continuum. The neural network policy description and continuum provided stratified network policy terminologies and syntaxes which formed the autonomic neural network constituency [**98**]. The policy-based EEG data management system was considered as fundamental in the control and coordination of semi-autonomous systems. This provided the basis for autonomous decision making processes for the EEG neural network system [**99**]. The autonomic policy paradigms that are feasible in the control and coordination of semi-autonomous systems include:

Action Policy: In the programming of microcontrollers and embedded systems technology, the "IF" (specified conditions) "THEN" (actions) described the states in which the autonomous system was expected to engage in, provided the specified conditions in the action policy are met.

Goal Policy: This described the specific single state or criteria which may trigger an action in the semi-autonomous system. The goal policy utilized binary classification scheme of "1" or "0' to describe the desired state or the undesired state respectively

Utility Function Policy: This measured and provided real-valued states of the autonomic neural network system. It provided the sense of satisfaction or dissatisfaction with the action executed by semi-autonomous system.

Each of the policies may be used independently to manage EEG data across neural networks. In order to ensure that the neural network exhibits autonomic network characteristics, the integration of all autonomic neural policies was essential. In figure 4-2, the global strategies of the autonomic network system is shown and figure 4-3 shows the proposed wireless architecture integration in the autonomic structure.

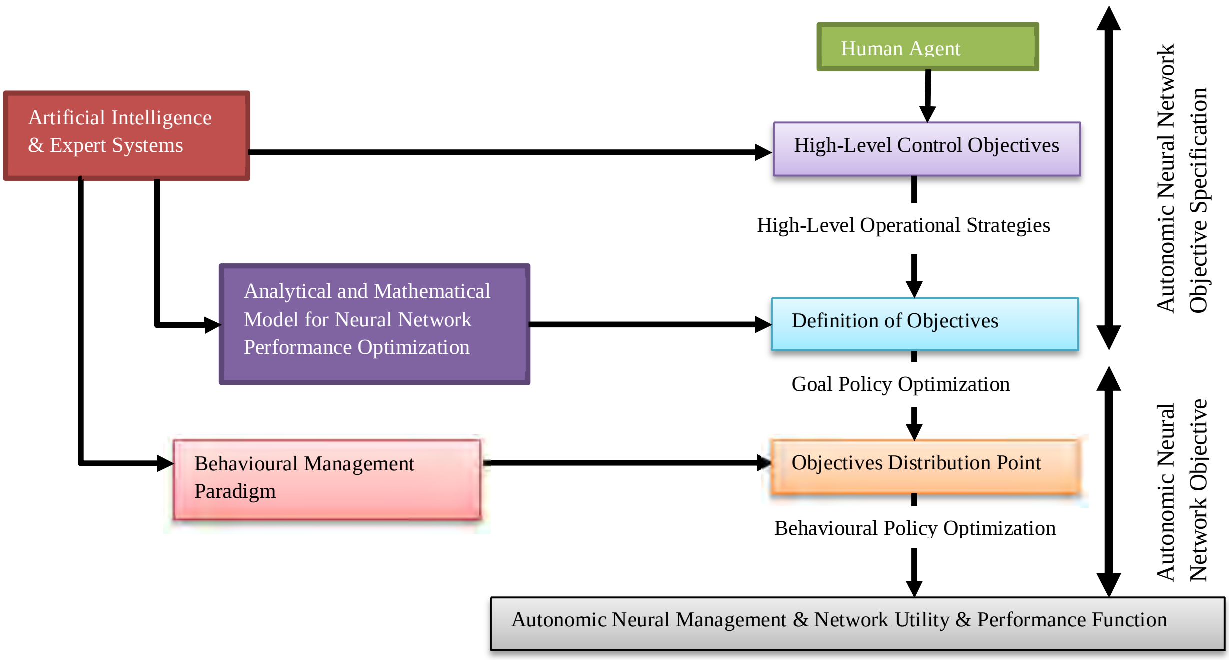


Figure 4-2: Global View of Autonomic Neural Network Structure

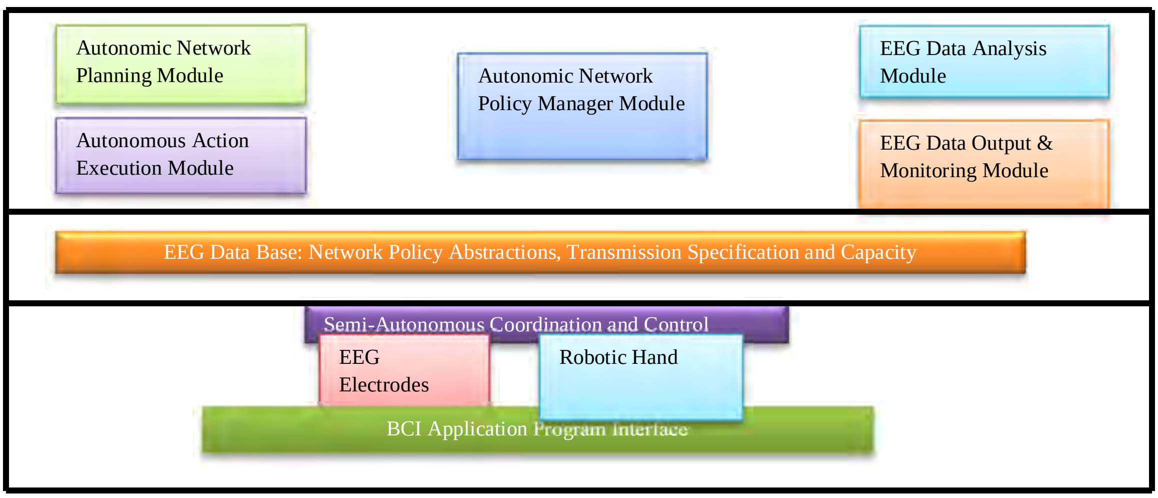


Figure 4-3: Proposed Autonomic Structure for Autonomic Transmission.

4.4 Action Observation Network

The EEG Action Observation Network (AON) was modelled to integrate and transform observed cognitive processes and thought processes originating from EEG signals into machine readable command codes. Due to its nature and characteristics, AON responded to biological signals [**100**]. The network was designed to automatically respond to the presence of EEG artefacts in the autonomic neural network. The imagination of motion movements, thought processes and cognitive processes of interest activates AON. The effective management of cognitive load on AON led to effective robotic and mechatronic system control. Behavioural activities capable of transforming cognitive activities into useful artefacts were of importance in the control of semi-autonomous mechatronic systems using autonomic neural network architecture. The matching of cognitive and behavioural activities played critical role in the tuning of AON in the autonomic neural network system. The preferential engagement of robotic motion or mechatronic system control showed that observed activities were critical in the development and tuning of AON [**101**]. Activities of interest within the familiarity continuum may be seen as part of the wider indicators of activators of AON. In the design and functional characteristic of each BCI system, AON network can be activated by wide variety of social behavioural activities.

Acquiring motion control skills was quite critical to the effective generation and activation of artefacts of interest for use in the BCI system. In order to effectively control the robotic or mechatronic system, the brain was trained to recognise certain actions when viewed or imagined. The observation of actions, activities, signs and the imagination of such behavioural and cognitive activities was the key to AON functional mechanism [**102**]. Close correlation and tuning of behavioural activities to cognitive activity and load were not easy to correlate. The relationship was difficult to establish as it was not easy to isolate behavioural observation and purely imagined activity. It was imperative that BCI users acquainted themselves with behavioural activities and actions that are able to efficiently activate AON. Visual inputs and imagined actions provided cognitive representations that evoked the potentials necessary and required in the control of robotic and mechatronic systems. Learning and training were critical processes of the BCI technology development. Adaptive learning in the AON autonomic system was proposed in the study. Adaptive learning in this study referred to the state where the AON autonomic system recognised observed patterns and actions. These activities were translated in the quickest and most accurate form irrespective of subject behavioural characteristics [**103**]. Behavioural pattern recognition in EEG signals representations were important especially in passive stimuli translation. Several neural sites responded to these observed behavioural activities in conjunction to physical training of motion movements. Interactions with objects and devices with our immediate environment stimulated neural responses [**104**]. The stimulation of neural responses activated AON for use in the control of semi-autonomous mechatronic systems integrated in within autonomic neural network system. The kinetic and mechanics of observed actions, learned actions and imagined action showed the importance of brain familiarity in generating the required EEG artefact for controlling mechatronic systems. It was evident that there was the coding of similar neural processes involved in the observed behavioural actions. These were mapped to the neural sites generating the EEG signal [**105**]. The pragmatic translation of the behavioural activities and imagined actions across the autonomic neural network created an efficient technique in the correlation of cognitive activity to robotic motion.

The influence of physical activities and movements on brain activity modulation has been proposed to affect the activation of specific neural site or brain lobe. Regular observation of activities and physical processes in the environment has been carried out both consciously and unconsciously with any specific motive [**106**]. In this study, having specific aims and objectives while observing physical activities created untapped neural resources in the development of BCI technology. Predictive cognitive mechanisms were fundamental to the effective integration of AON in autonomic neural network. It can be concluded that perspective, aim and transitivity when directed and coordinated adequately influenced the generation of EEG artefacts from specific brain regions. In order to effectively portray the concepts embedded in action observation network, it was noteworthy that action observation mechanisms were products of the cognitive activity type and sensory processes in the primary motor regions. The simulation of actions, activities and tasks are fundamental to the common performance of the autonomic neural network substrate [**107**] [**108**]. The integrative approaches presented in the study were intertwined with the various segments of the BCI and were reliant on sensory motor performance and articulation. With predictive coding, observed actions were simulated facilitating the modulation and increase the efficiency of AON system.

4.5 Materials, Methods and Experimental Setup

The experimental setup for the study included subjects chosen at random. The subjects were assumed to be free of any neurological complications. Microelectrodes were used in the recording of electrical signals from the brain. This provided means of measuring high spatial and temporal resolute electric discharge patterns with minimal nervous tissue damage. It also provided the desired technique for analysing and observing the functional behaviour of neurons and the transmission of EEG signals in autonomic neural networks towards developing robot control commands [**109**].

4.5.1 EEG Recording Setup

Before the distribution of EEG signals could be effectively investigated, it was essential that the participants were relaxed and cooperative in the tasks that were associated with the recording of the signals. Emotionally disturbed individuals were relaxed through friendly conversation as the electrodes were placed on the scalp. Questions about electrode feel and painless nature of the exercise were administered during electrode placement. EEG recording instruments have high sensitivity and as such, large series of unwanted brainwaves such as artefacts from scalp muscles, eye muscles and heart were also recorded. Included also in the recorded data were noise from nearby electronic instruments and media. The attenuation of specific brainwaves filters the signal allowing the desired EEG artefact to be investigated while leaving unaffected frequencies. Low frequency and high frequency filtering were applied at various stages of EEG signal analysis. The low frequency filters controlled the response of the EEG recording instrument at low frequencies while its response to higher brainwave frequencies was unaffected. The high frequency filters controlled the response to high frequencies while lower frequencies remained unaffected. The procedure implemented ensured that the subjects were assessed for EEG signal characteristic control. EEG recordings were conducted on handful of subjects while they performed simple mind related activities. The electrodes were placed in accordance with the 10-20 system [**110**] of the International Federation for recording two homologous channels of EEG data. Spectral power analyses were performed on the various segments of the recorded data. The spectral power values were averaged together [**87**]. The full configurations used during the study to record and investigate EEG signal analysis are shown in figure 7-3 and figure 7-9 in chapter 7.

4.5.2 Electrode Placement

The standard international 10-20 electrode placement system as shown in figure 4-4 provided the framework and basis for placing electrodes on the scalp. It provided the standard procedure for equally placed electrode position measurement on the scalp using identifiable skull landmarks as reference points. Differences in skull sizes were catered for within 10% or 20% of measurements between skull landmarks. The nasion, inion and two preauricular points are the four landmarks for the 10-20 system framework. The nasion represents the indentation between the forehead and the nose bridge. The inion represents skull protrusion felt as the hand is run up the neck to the base of the skull [**111**].

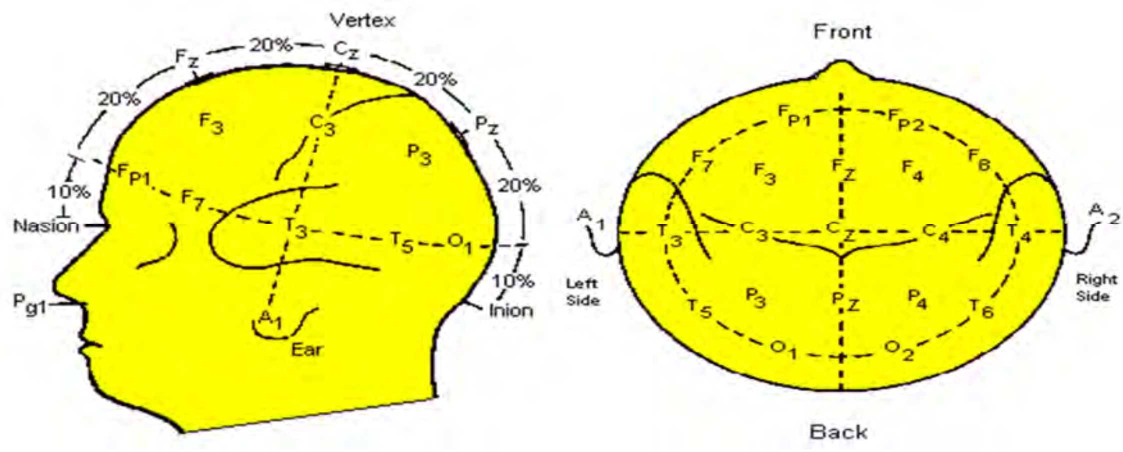


Figure 4-4 : 10-20 System Electrode Palacement Landmarks

4.5.3 EEG Electrode Array

EEG sensor array measured the bioelectric wave-fields associated with neural firings extracting information from the neuronal bioelectric sources. The EEG sensor array identified the medium through which the bioelectric wave-field propagated. It was critical to understand the governing bioelectric wave-field models governing EEG electrode array signal processing. In the ideal homogeneous open space medium and high frequency signal processing, thorough wave phenomenon may not be required. Given that EEG signals were observed at relatively low frequencies and were bounded in mediums which may be inhomogeneous, wave physics was useful in providing insights. The array of EEG electrodes distributed over scalp received propagating bioelectric wave-field with following aims:

- Localization of the EEG source.
- Reception of bioelectric information from near neural signal sources.
- Imaging of the medium through which the bioelectric wave-field propagates.

4.5.4 EEG Source Estimation

Bioelectric signals radiated by neural sources are separated by the principle of non-overlapping or partially overlapping temporal spectral characteristics. Spatio-temporal EEG signals had spatial spectrum as additional variability degree in their signal characteristics. The differences existing in the spatial spectra and temporal spectra were critical elements in the separation of EEG signals. EEG signals were sensed from widely different directions on the human scalp. These may have non-overlapping spatial spectra and the array of EEG electrodes was used in the identification and separation of EEG signals. It was worthy to note that when the EEG signal sources were considered to be quite close, perfect signal separation was impossible. There were some forms of cross-talk between the EEG signals as their frequencies overlapped. In view of signal cross-talk, Finite Impulse Response (FIR) filter was useful and efficient in analysing EEG signal cross-talk power in relation to EEG signal power. In the search for useful EEG signal, unwanted signals or interference were suppressed by placing null or the collection of nulls in the spatial frequency band occupied by the unwanted signal or interference. The robustness of the nulls placed in the EEG spatial frequency was enhanced by introducing additional constraints in the FIR filter. Useful results were derived from such filter constructions in the analysis of EEG signals such that unity filter response was the indication of useful EEG signal. Another filter of critical importance in the analysis of EEG signals was the Capon's filter [**112**]. Capon's filter was introduced in the analysis under the assumption that EEG signals and interference signals that may be present are highly directional. Capon's filter provided the minimum variation between EEG signal and their corresponding interference sources. With Capon's filter, sharp nulls were placed at the spatial frequency corresponding to the interference signal and in any direction the interference source may appear. The null Capon's filter used the principle of null steering to supress varying EEG signal interference.

4.5.5 EEG Headsets

To record, extract and classify EEG signal for robotic control, the Neurosky Mindwave and Emotiv Epoc EEG headsets were used in acquiring the EEG signals. EEG data were transmitted in both headsets wirelessly. The Neurosky Mindwave shown in figure 4-5 [**113**] utilized an RF module for EEG Data transmission to the computer. The Neurosky Mindwave transmitted the EEG data wirelessly at the sampling rate of 512 Hz over the 2.420-2.471 GHz RF range. The RF data rate was at 250 kbit/s. The single electrode placed at the forehead detected the five primary brainwaves. These brainwaves are namely delta, theta, alpha, and beta and gamma waves. In summary, the autonomic neural network developed with the Neuraosky mindwave made use of the single EEG electrode capable of threading into five distinct brainwave channels for brainwave prediction and EEG artefact extraction. The single electrode can detect all available EEG signals at the frontal lobe of the brain.

Figure 4-5: Neurosky Mindwave

The Emotiv Epoc headset shown in figure 4-6 [**114**] has fourteen electrodes for EEG signal acquisition. The electrodes were placed on the user's head according to the international 10-20 EEG electrode placement system. The Emotive Epoc utilized the sequential sampling method at the sampling rate of 128 Hz and at the resolution of 16 bits at 0.21µV. The Emotiv Epoc bandwidth ranged between 0.2- 45 Hz at 50 Hz or 60 Hz power supply. The EEG data was transmitted wirelessly over 2.4 GHz frequency band. The Emotiv hardware was capable of detecting brainwaves of five primary sections of the human brain. The brain sections where the EEG electrodes were placed are the frontal lobe, temporal lobe, central lobe, parietal lobe and the occipital lobe. The placement of the 14 EEG electrodes in these locations allows for the detection of 14 distinct EEG signals for processing and transmission in the autonomic neural network.

Figure 4-6: Emotiv Epoc Headset

4.6 Results and Performance Investigations

The performance of the wireless autonomic EEG network was evaluated using the Bit Error Rate (BER) for the wireless EEG network transmission. The EEG data was passed through Additive White Gaussian Noise (AWGN) using flat Raleigh as the fading channel. The performance was evaluated using the AWGN as reference point. The result shown in figure 4-7 implied that the lower the SNR of the EEG wireless network the higher the probability of error in transmission EEG data across the autonomic wireless network and vice-versa.

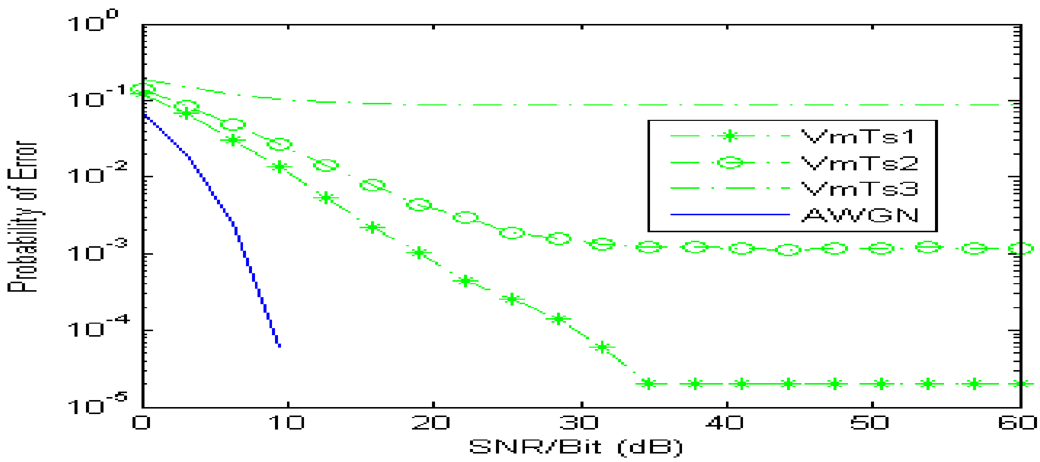


Figure 4-7: EEG Wireless Autonomic Network Bit Error Rate Performance Throughput

In using an adaptive linear equalizer in evaluating the channel transmission performance for the RN-171-Xv wireless modules and X-bee Pro wireless modules in transmitting EEG data over the autonomic wireless network indicated that the network BER reduced as the SNR of the network increased to 20 dB and stabilised thereafter. The wireless network taps were influential in the lowering and increasing the BER. The wireless EEG network taps were indications of feedback sequences required to overcome EEG signal interference. The higher the network taps the more unstable the wireless autonomic transmission of EEG data. In figure 4-8 the throughput results of the effects of the adaptive wireless network equalizer on EEG data transmission over autonomic network is shown.

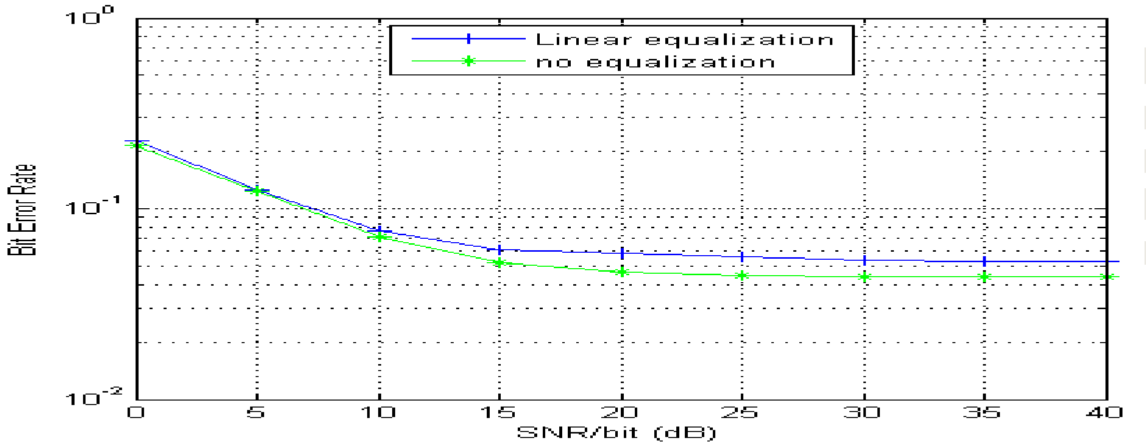


Figure 4-8: Adaptive Linear Equalizer on Wireless Autonomic Network Transmission

In figure 4-9, results from the autonomic wireless network decision feedback mechanism is shown. The throughputs from the autonomic wireless network implied that coherent demodulation of the wireless network decreased the BER of the wireless network given that the network data transmission phase was in perfect synchronization.

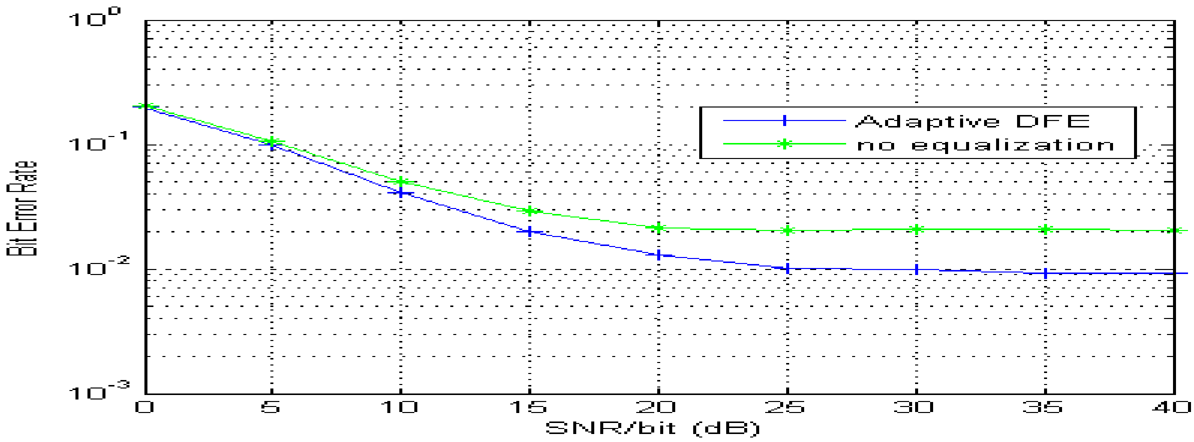


Figure 4-9: Autonomic Wireless Decision Feedback Equaliser Throughput Performance

Increasing the path loss parameter of the EEG autonomic wireless network resulted in fewer EEG data being managed by the wireless autonomic network. Lowering the path loss parameter enabled the autonomic wireless to manage more EEG data efficiently. The findings are presented figure 4-10 and the signal amplitude peaks at 0.7 while in figure 4-11 the findings indicated that the signal amplitude peaked at 1. The transmission efficiency of EEG data was influenced by the wireless network path loss parameter.

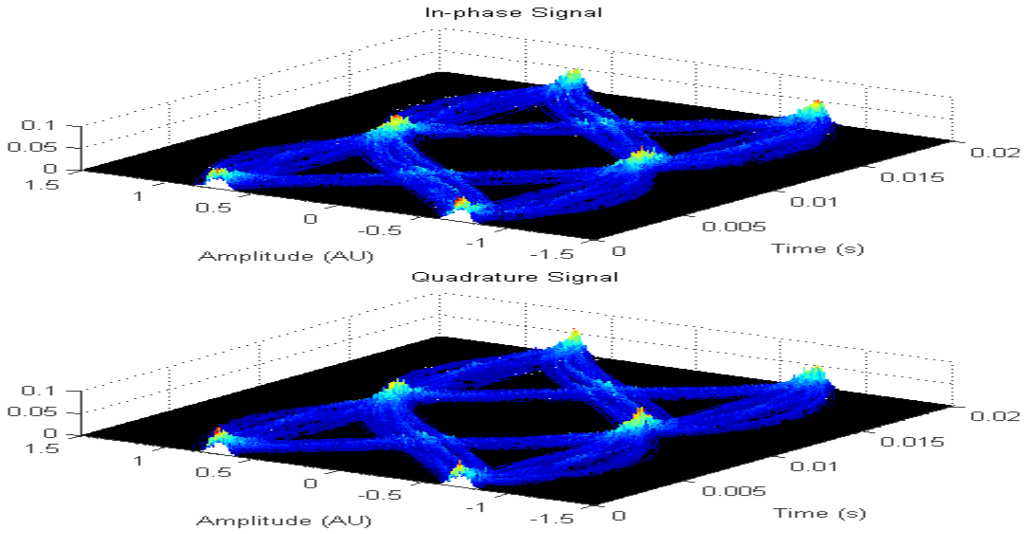


Figure 4-10: AON-Autonomic Wireless Network Performance Throughput with higher path loss

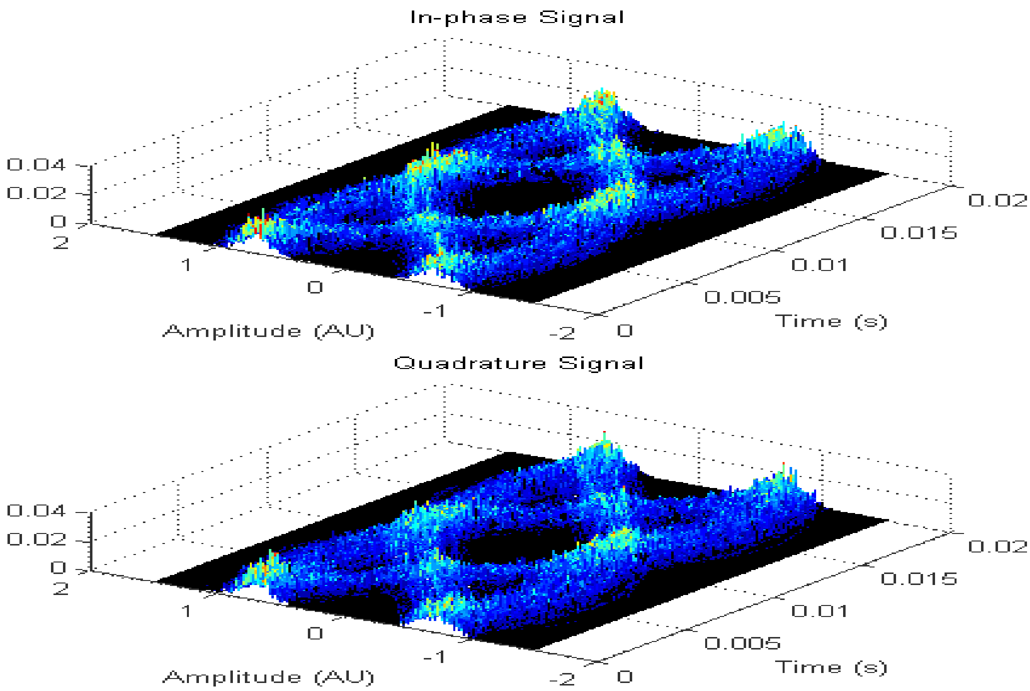


Figure 4-11: AON-Autonomic Wireless Network Performance Throughput with lower path loss

4.6.1 Fiducial Definition and Representation

In estimating EEG signal source in an individual, it was paramount that the EEG signal source fiducials were estimated and determined. This provided some form of signal tracking and signal source fiducial identification carried out on the individual when EEG electrodes were placed on the scalp. EEG source fiducials[20] and the fiducial selection were used in EEG signal source identification and electrode

[20] MRI image analysis reference points and coordinate system definition points

placement preparation. Brainstorm software was used in the EEG source estimation analysis. In the Brainstorm there are three possible fiducials which were used independently or simultaneously during EEG signal analysis. The default Brainstorm fiducials were based on *Colin27* MRI developed by Montreal Neurological Institute (MNI) [**115**] [**116**]. The Colin 27 MRI head volume was based on an average of 27 T1 scans of Colin Holmes brain [**117**] [**118**]. The MRI reference points necessary for EEG signal source estimation included the following:

- Subject Coordinate System (SCS): The SCS reference points take into account the Nasion (NAS), Left Pre-Auricular point (LPA) and the Right Pre-Auricular point (RPA).
- Normalised Coordinate System (NCS): The NCS reference points include the Anterior Commissure (AC), Posterior Commissure (PC) and the Inter-Hemispheric point (IH).

In conjunction with the aforementioned coordinate system, the Cartesian coordinate system (x, y, z) was also managed by both the SCS and NCS systems. The reference points and the coordinate systems are shown in figure 4-12. The data used in the simulations were electrical simulations of hand movements, eye blinks, smirking, and smiling. The EEG data contained an average of 100 trials. The principle behind the large number of trails was to determine the primary sensory response on the brain cortex. The human head and brain were modelled for simulation purposes. Figure 4-13 shows the model of the brain cortex. At the importation of the head and cortex models as surfaces, an MRI registration process was carried out on the models to determine the coordinate system of the head and cortex models and register the models with standard or defined MRI specifications. The MRI registration process interpolated the head and cortex models with standard or custom MRI volume specification. In figure 4-14, the yellow lines in the merged head and cortex models indicated re-interpolation of the head and cortex surfaces in the MRI volume.

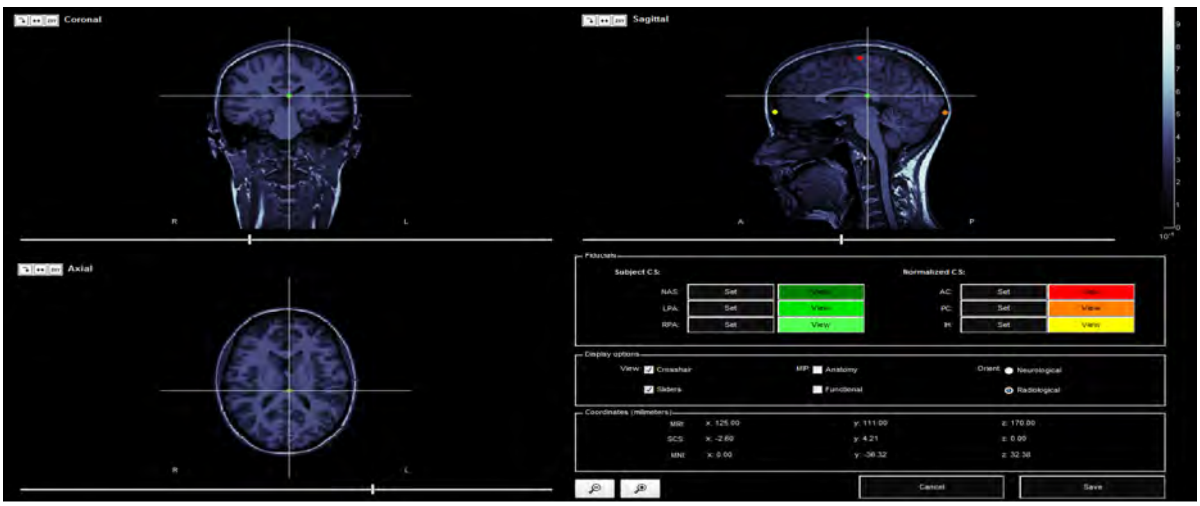


Figure 4-12: MRI Coordinate System Setup and Definition

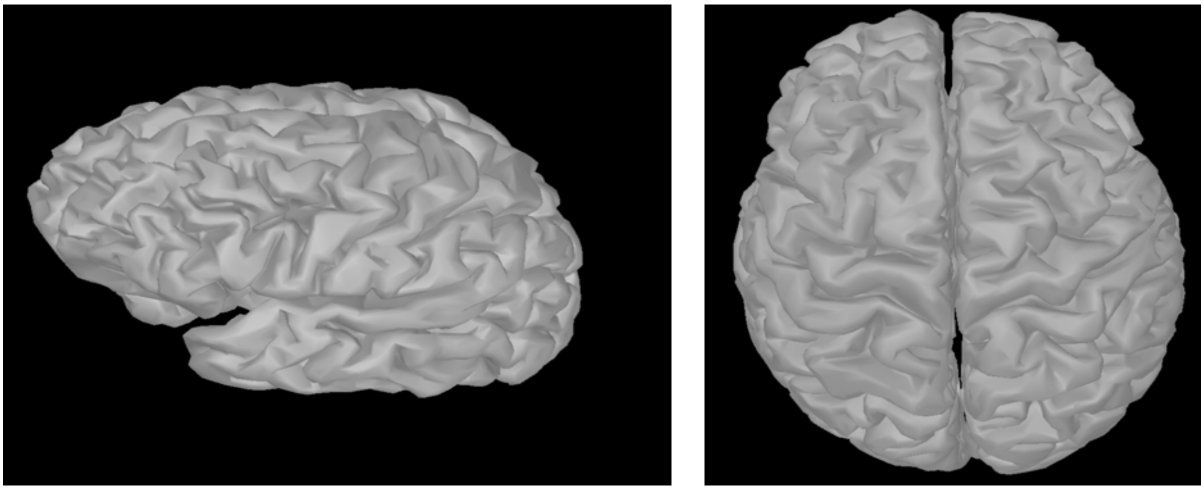


Figure 4-13: Brain Cortex Model

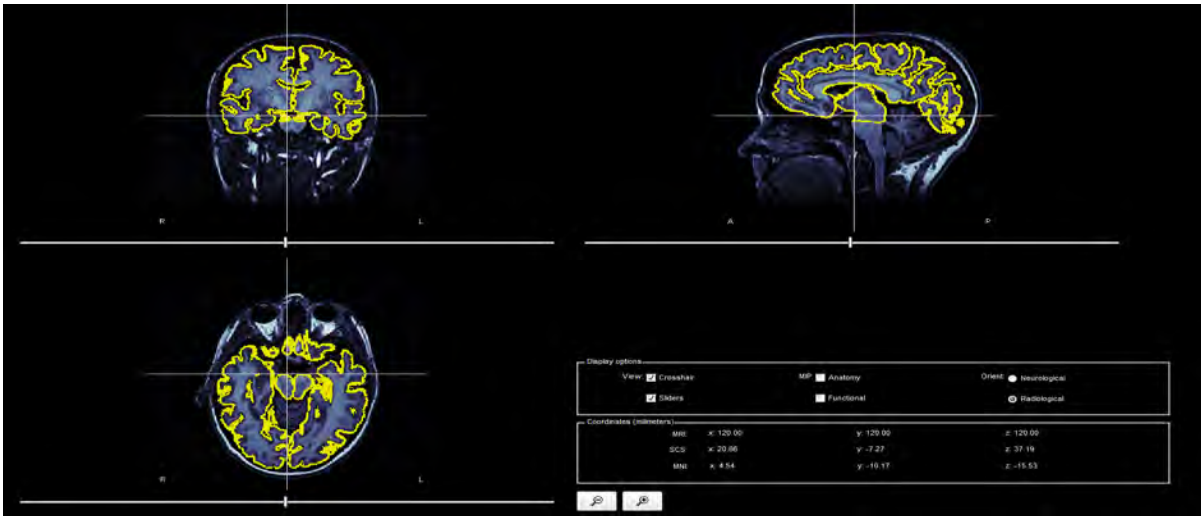


Figure 4-14: Head and Cortex Registration with MRI Volume

Recorded EEG data were imported with all epochs associated with each EEG electrode average in time. The averaging of the EEG data eliminated sensor baseline effects on the recorded data. This can also be achieved through the use of high pass filter at a very low frequency while the data was being recorded. In figure 4-15, the positions of the EEG electrodes were modelled as nested helmet. The activities of each brain section characterised by the sensor is shown in figure 4-16.

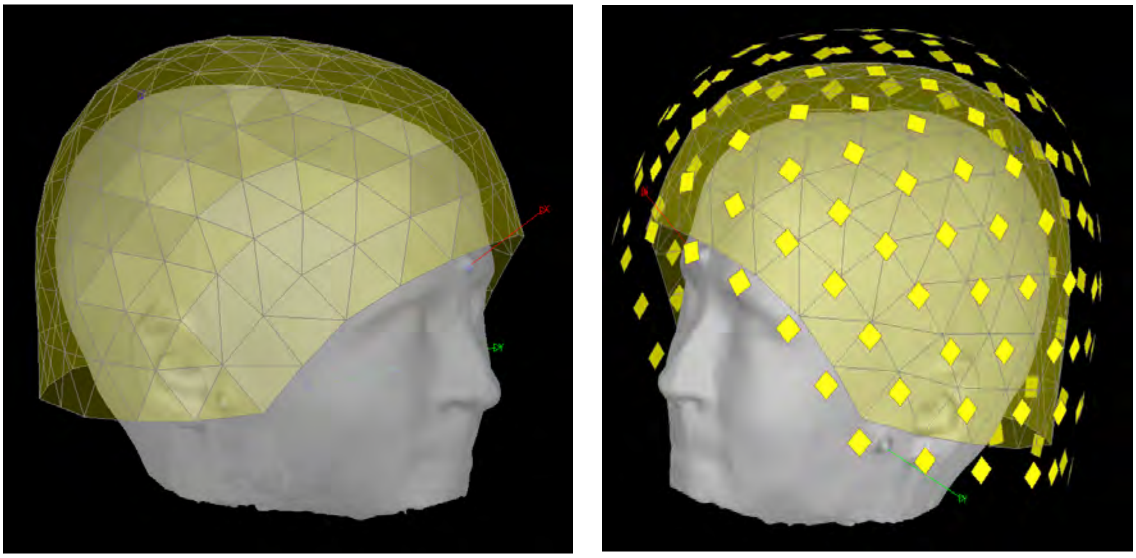


Figure 4-15. EEG Electrode Position Model

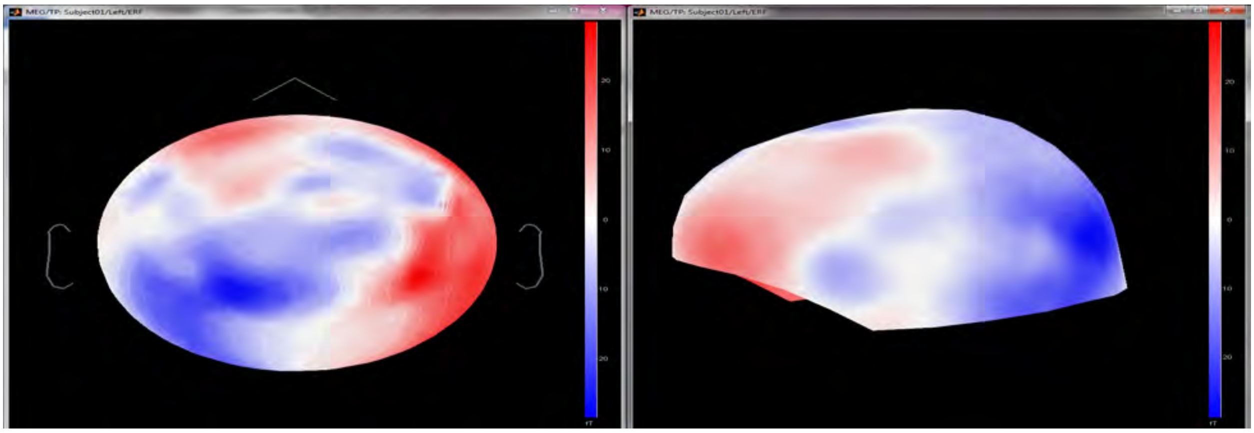


Figure 4-16: Brainwave Sensor Characterisation

4.6.2 EEG Source Estimation Results

In the estimation of EEG signal source, an implementation of the forward model matrix derived from the head and cortex models were used in the identification and computation of EEG signal source. Minimum-norm estimation was implemented in the estimation and determination of the EEG signal source. The minimum-norm estimation implemented time series linear algorithm on each of the EEG signal source. This made the computations efficient in their use. The minimum norm estimation process isolated the source of each signal in the cortex model. The sources were efficiently identified as shown in figure 4-17. Figure 4-17 shows both the signal time series and the signal source origin on the brain. There are also other useful algorithms which were also investigated during the source estimation process. The algorithms include the noise normalised estimate using dynamic statistical parametric mapping and standardised low resolution brain electromagnetic tomography.

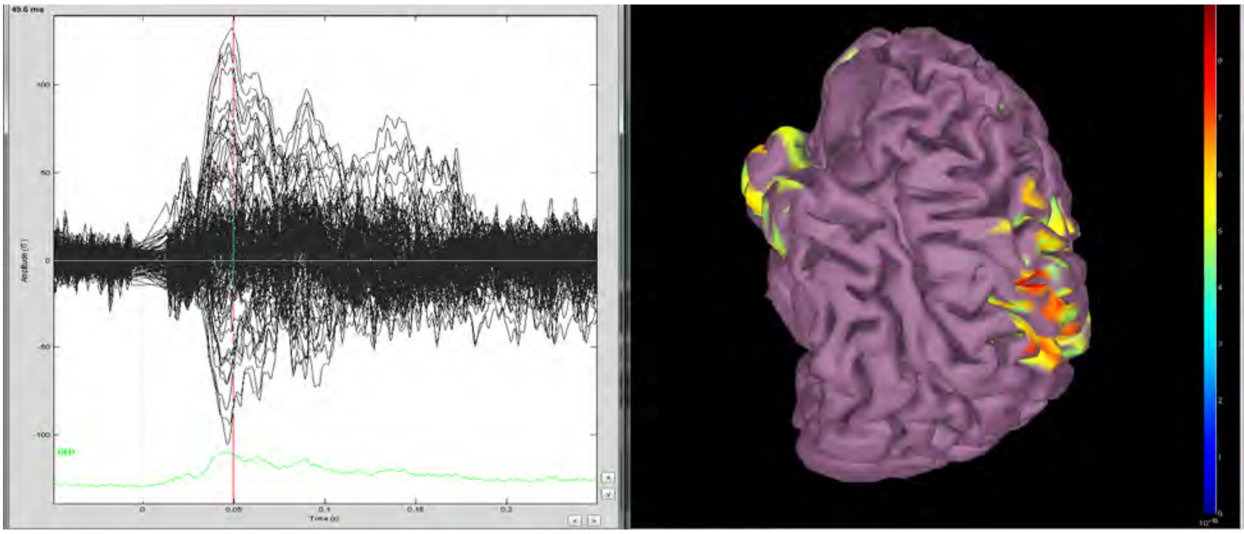


Figure 4-17: EEG Signal Source Estimation

4.6.3 Scout Analysis

Scout analysis describes the analysis that focused on areas or Regions of Interest (ROI) on the surface of the cortex. In the analysis of EEG signal source, regions of interest were created in order to facilitate the investigations on specific brain activity. The aim of creating scouts was to determine the average neural activity in the selected area of interest.

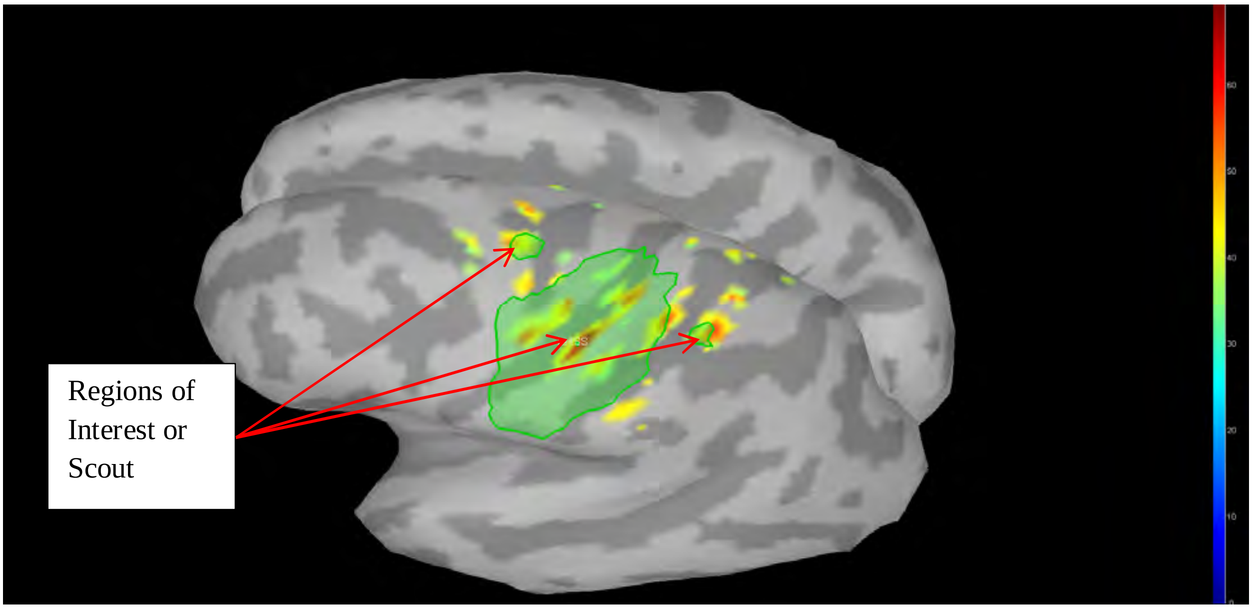


Figure 5-18: Regions of Interest

In the scout analysis, Principal Component Analysis (PCA), average of absolute EEG signals, average of power signals, signal maximum amplitude or the mean of EEG data were instrumental in the analysis of the signals as indicated in figure 4-18 .The type of results desired and areas of interest influenced the choice of functional analysis during scout analysis. Performing scout analysis on EEG signals brought together all identified vertices in the cortex and aggregating functions such as the signal power, PCA etc. in exploring brain activity in the different brain regions. The brain regions include prefrontal, frontal, central, pariental, temporal, occipital, limbic, right and left hemispheres. Custom regions were also created for experimental purposes. Figure 4-19 and figure 4-20 shows comparisons in EEG signal amplitude with power values and mean algorithm. Similar result profile was realised in the analysis.

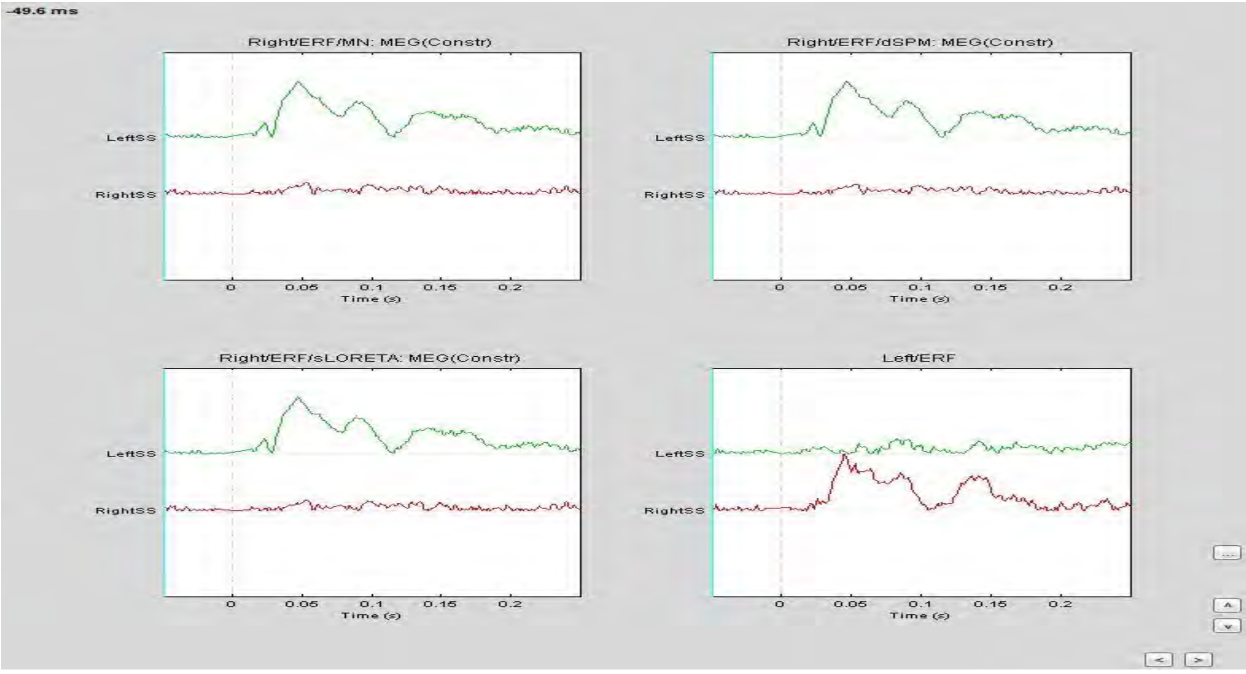


Figure 4-19: Scout Analysis with Mean Algorithm

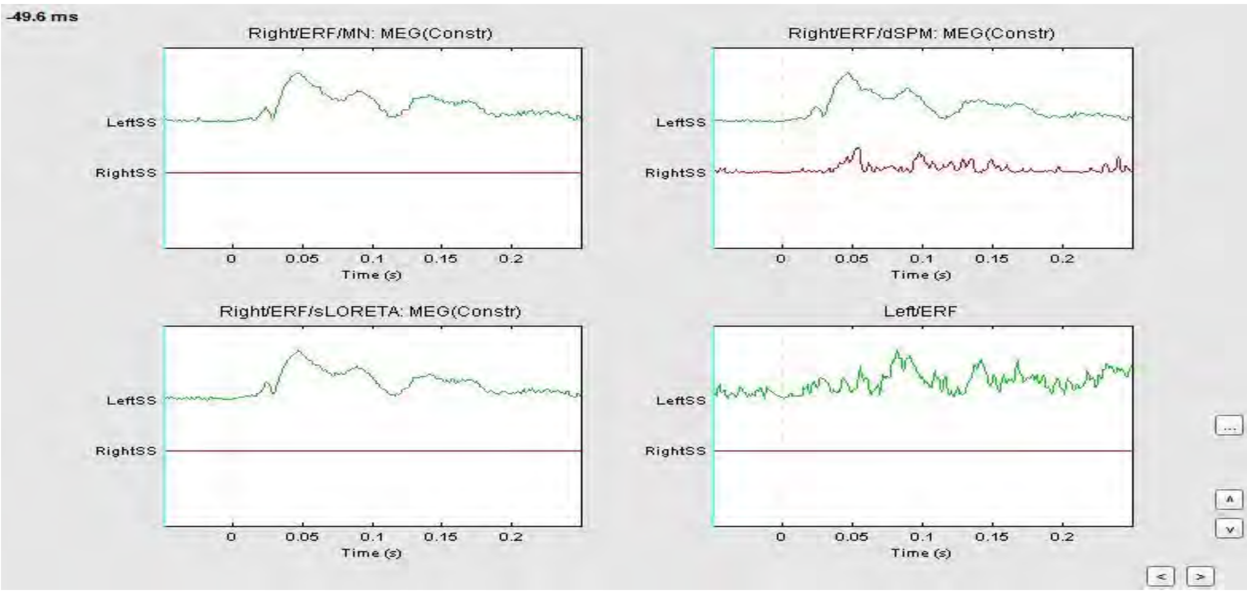


Figure 4-20: Comparing Max Amplitude with Signal Power Values

4.7 Summary

The chapter discussed the integration of wireless autonomic neural network with action observation network. The action observation architecture ensured that information and data from signal source were matched to signal outputs within the autonomic neural network. The relationship between cognitive task and robot control commands are established using the AON augmented in the EEG autonomic neural network. The EEG wireless autonomic system relied on the effective placement of EEG electrodes on the scalp. Regions interest on the scalp was used to investigate the acquisition of specific EEG signals from the brain. The results discussed in the chapter provided the necessary framework towards effective electrode placement on scalp, EEG signal source detection, acquisition and sensor noise reduction. The transmission of bio-signals through wireless autonomic architecture required the computing subsystem, transmission subsystem and sensing subsystems. These subsystems provided different levels of data and information management systems in the autonomic EEG wireless network architecture. The results presented in this chapter provided the framework in determining effective EEG electrode placement and EEG data recording setup. This ensured that correlations in the data management process in the autonomic neural network were effectively monitored against transmitting noisy EEG signals. The work presented in chapter four was performed in order to develop the desired motor control codes for controlling the robotic hand using AON and investigate the performance of the wireless autonomic neural network in transmitting the motor control codes.

CHAPTER FIVE

EEG Artefact Identification, Extraction and Classification Modelling In Adaptive Neural Networks

The chapter discussed the modelling of EEG artefact identification, extraction and classification using various algorithms. The identification of EEG artefact suitable for semi-autonomous coordination and control applications were implemented using independent component analysis and Bayesian algorithm. Event-related potentials augmented with radial basis function kernel were also integrated in the identification of EEG artefact. The models used in the extraction and classifications of EEG data include: radial basis function classifier, linear discriminant analysis, principal component analysis, singular value decomposition, and logistic regression algorithm. The EEG feature extraction kernels include: wavelet transform algorithms and multilayer perceptron algorithm. The EEG data filter integrated was the finite impulse filter. These algorithms provided the necessary integration and augmentation technology required for the identification, extraction and classification of EEG data for control applications.

5.1 Introduction

The amount of information the brain can handle cannot exactly be quantified. The reason for this lied in fact that the human body acted as the complex sensory network system for recording, analysing and interpretation of physiological signals. EEG signal was one of the signals of particular interest in the study. The signals acquired and released by the human body system were the reflections of the human brain activity. The oscillatory characteristics of EEG activity reflected the synchronization of large number of neurons and the order of rhythmic activation of the signals on temporal basis. The various oscillatory states of EEG signals were indicative of the information processing and transmission states. The oscillatory states of EEG activity and the rhythmic synchronisation of the waveforms provided an avenue for the enhancements. The enhancements were in learning, perception and transmission of EEG signals from and between different regions of the human brain [**119**].

The objective of brainwave feature extraction components was to develop an adequate representation of the bioelectric brain signal. This enabled the simplification, classification or detection of specific brain activity associated with human thought process. The characteristic function of the feature extraction process was to encode the intended commands sent by the subject. The process ensured that the signal was not contaminated with noise that may be present and had the ability of inhibiting the classification process. The brain signal classifier used the identified brain signal features to assign the recorded brain wave samples to the particular mental pattern. The classification of brainwave signals was one of the crucial processes that were associated in the development of a robust BCI system. Due to the intrinsic dynamic nature of EEG signal oscillatory properties, traditional spectral analysis was deemed not suitable to quantify the various oscillatory activities. The non-stationary characteristics of EEG signals required that Time-Frequency Representations (TFR) of the signal contents were implemented. The BCI communication interface system allowed the subject to communicate with the computer. The classification of EEG signals in verifying the subject's physiological hypotheses formed the two main categories in EEG signal classification. The EEG signals had certain properties which were analysed using the following procedures [**120**]:

1. Electrode selection
2. Spartial pre-filtration
3. Choice of relevant parameters
4. Optimisation of parameterisation procedure and model construction
5. Optimisation of classification procedure

5.1.1 Chapter Motivation

The work presented in chapter 5 was performed in order to showcase the individual performance of the subsystems of the EEG identification, extraction and classification model. Each subsystem has its advantage and disadvantage in EEG identification, extraction and classification. Integrating the subsystems in a particular fashion leverages their advantages and minimises their disadvantages in developing an efficient system. The Bayesian search paradigm was used in the EEG analysis system as it provided a two-state decision making system in selection of EEG artefact. The integrated EEG identification, extraction and classification model is presented in section 5.13.

5.2 Independent Component Analysis (ICA)

Improvements in human brain imaging methods increased research activities into neuronal activities that generate electrical potentials on scalp. These potentials were analysed using time series techniques to reveal the spatial distribution of the brain potentials. Biophysics principles suggested that temporal coherent activities in any brain area created far-field potentials on the scalp and were widely distributed across the scalp. The EEG signals were tapped off from the scalp as the total of all the activities that occurred at the EEG source areas. The source areas included the electrical artefacts from eye, electrodes and muscle movements. Independent component analysis technique decomposed multi-channel EEG data into independent component processes that described brain generated activities or non-brain artefacts[21]. Each brain and non-brain component activity was identified with a time signature and sets of relative strengths of conductions to the recording electrodes.

Brain imaging complexities arose as a result of the differences that existed in the cortical folding of each human being. Cortical patches had net source orientations and locations. Each individual produced disparity in the orientations of spatially equivalent source areas. This produced large disparities in the associated projection on the scalp [**121**]. These differences also gave rise to the EEG inverse problem[22]. The inverse problem necessitated the development of other techniques for monitoring spatially generated electric field potentials on the scalp. One of such signal processing alternative was the Independent Component Analysis (ICA). The ICA allowed for simultaneous monitoring of spatial field activities in different cortical regions. The ICA method to dynamic brain imaging was aimed to separate independent EEG activity in each individual. This was performed by using information content of the EEG data to separate portions of the recorded scalp data. The recorded data were from the active artefact and cortical source area. These were based from plausible physiological and statistical assumption given that these activities were nearly independent of each other over time. The spatial and temporal properties of the ICA processes followed the following assumptions:

- The component source locations and their scalp sensor topographic projection pattern were fixed throughout the data.
- The linear sum of the projected component source activities occurred at the sensors.
- There were no differential delays associated with projecting the source signals to the different sensors.
- The probability distributions of the individual component source activity values were not exactly Gaussian.
- The component source activity waveforms were maximally distinct from each other or maximally temporally independent of each other.

The temporality independence of the EEG signals described the activity values of any subset of the EEG signals. At any given time, temporal independence provided no evidence about the activity values of any subset of the remaining sources at the same time. This made each component source signal an independent source of information in the EEG data. This supplied temporal pattern that was not in any fashion determinable from the values of other component source signals [**122**]. EEG analysis were carried out under the general and physiological plausible assumption that far field potentials were detected at the scalp and not generated on the scalp itself. The assumption also states that potentials

[21] Brain and non-brain artefacts include activities such as eye blinks, associated eye movements, heart muscle activity, scalp or other environmental noise.
[22] EEG inverse problem describes the difficulty of locating brain sources of recorded EEG data and it is resolved using certain assumptions and constraints.

were generated within spatial fields of analogous oriented cortical pyramidal neurons. EEG recording occurred as the time series of measured potential difference between an active electrode and a passive electrode[23]. The inception of EEG source field started when the pyramidal cells in the given cortical region produced far-field potential. The produced far-field potential was as the result of the partial synchronisation of the surrounding local fields [**123**].

5.3 EEG and the Radial Basis Function Neural Network

Radial Basis Function (RBF), the class of neural functions provided the necessary kernel required for interpolation and classification of EEG signals suitable for various BCI applications [**124**]. The computation time required for learning in radial basis function neural network was less in comparison to other neural networks. In principle, RBF can be used in either linear or non-linear signal model and single or multi-layer networks. The nonlinearity of RBF network was expressed in terms of the basis function not being constant in the event that there was more than one hidden layer. The position and size of the basis function defined the nonlinearity of RBF network. The refining of global variable provided suitable mappings in the refining of local feature in the RBF neural network [**125**]. The network variables were characterized by their centre (ω) and width (σ). The response of each hidden unit in the neural network with input $X, X = [x_1, x_2, \dots., x_n]^T$ was modelled as:

$$\phi_k(X) = exp\left(-\frac{1}{\sigma_k^2}\|X - \omega_k\|^2\right) \tag{5-1}$$

where ω_k represents the center variable for the kth hidden component, σ_k represents the Gaussian function width. The network output layer performed simple summation for the network. The response for each hidden unit scaled by its corresponding weight (α) to the output node produced the overall network output when summed up. The total network output was modelled as:

$$f_m(X) = \alpha_{mo} + \sum_{k=1}^{N} \alpha_{mk}\phi_k(X) \tag{5-2}$$

where N represents the total number of hidden neurons in the neural network, α_{mk} represents the corresponding kth hidden unit weight mapped to mth output node. The corresponding mth output neuron has α_{mo} as the bias term. The radial basis function neural network allowed for the tuning of network parameters and allocation of hidden network units. Radial basis function neural network has the capacity to accommodate more neurons than the standard feed-forward back-propagation neural networks. The robustness of the RBF network was increased as the number of training neural vectors increased. In mapping EEG signals and evoked potential, it was important to determine spatial features of the EEG signal. The topographical features of EEG signals provided the required access to the

[23] The passive and active electrodes are equally receptive to all cortical and artefact source signals.

detection of EEG signal in relation to localized brain activity [**126**]. The architecture of the RBF network was such that it had an input layer, pattern layer, summation layer and an output layer. RBF neural network for EEG signal classification can be a two-stage process as indicated in figure 5-1 [**127**].

The RBF neural network classification performance was evaluated and monitored using the mean square error technique. The Mean Square Error (MSE) technique for the RBF network is defined as [**128**]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(O_i - T_j\right)^2 \tag{5-3}$$

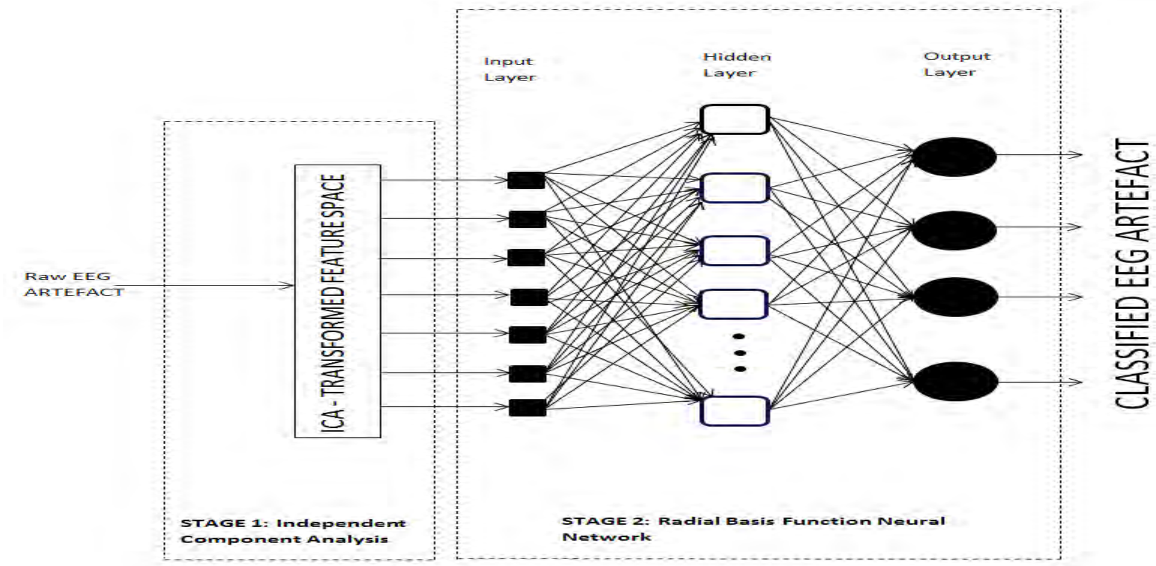


Figure 5-1: Four-Class EEG Classification Using Two-Stage RBFNN Classifier

where O_i represents the observed EEG frequency value at time i, T_j represents the target EEG frequency value at model classification/specification j, N represents the total number of observations per EEG epoch. The minimum MSE on the RBF network decreases as the number of the hidden units in the RBF network increases. The optimum number of hidden units provided the lowest MSE. Increasing the RBF hidden units beyond the lowest MSE deteriorated the network and increased the complexity of the RBF network. The performance of the RBF network was best achieved at the lowest MSE. The performance index for the RBF network was modelled as [**128**]:

$$PI = \frac{PC-MC-FA}{PC} \times 100 \tag{5-4}$$

5.4 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) provided high-dimensional data analysis for supervised machine learning. Data classification and dimensional reduction were performed using linear discriminant analysis. EEG data were randomly generated data and unequal frequencies were grouped into classes. LDA had the functional capacity to examine the different classes of EEG signal frequencies. The LDA technique maximized the ratio between EEG-class variance and within-EEG class variance. The LDA technique ensured optimum separation of the EEG artefacts [**129**]. LDA used optimal low-dimensional space to project different EEG data class during data classification process. This process facilitated EEG feature extraction before EEG data were classified [**130**].

The prime Objective of the LDA technique was to perform dimensional reduction on EEG data while preserving the discriminatory EEG artefact class information. For each of the EEG artefact class, their linear function attributes were computed. The EEG class function yielding the highest score represented the predicted EEG artefact. The LDA technique optimized predicted EEG artefact without multiple passes over EEG data [**131**]. LDA provided the probability estimates for each of the EEG artefacts. In comparison to Principal Component Analysis (PCA), LDA produced linear functions required for EEG data reduction. Given that LDA maximized the following objective:

$$J(w) = \frac{w^T S_B w}{w^T S_w w} \tag{5-5}$$

where S_B represents the “between EEG artefact-classes scatter matrix” and S_w represents the “within EEG artefact-classes scatter matrix”. The EEG artefact-class scatter matrices were modelled as:

$$S_B = \sum_c (\mu_c - \bar{x})(\mu_c - \bar{x})^T \tag{5-6}$$

$$S_w = \sum_c \sum_{i \in c} (x_i - \mu_c)(x_i - \mu_c)^T \tag{5-7}$$

where $\bar{x}$ represents the overall EEG data-cases mean and μ_c represents each case-mean. The sum of the EEG data matrices and mean vectors are constrained by,

$$\frac{1}{C} \sum_{i=1}^{c} \mu_i = \mu \tag{5-8}$$

S_B will be of rank (c -1) or less. The total scatter matrix for EEG data projections was given as:

$$S_T = \sum_{\forall x} (x - \mu)(x - \mu)^T \tag{5-9}$$

where

$$S_T = S_B + S_w \tag{5-10}$$

The EEG data projections having maximum frequency distinct class information were the eigenvectors corresponding to the largest eigenvalues of $S_w^{-1} S_B$. The solution optimized the linear discriminant analysis technique and provided efficient solution to the classification of EEG data [**132**].

5.5 Principal Component Analysis

In classifying EEG artefacts, it was deemed necessary to obtain adequate measures of tendency from the observed EEG artefacts. From the observed EEG data characteristics, smaller EEG data variables known as EEG data principal component were developed. These accounted for variances in the observed EEG data variables. The EEG data principal components were then used as the bench mark in the EEG data analysis and classification process. The aim of principal component analysis was to reduce the number of observed EEG epochs into relatively smaller number of EEG artefacts while retaining important information contained in the EEG data. Principal component analysis served to simplify the description of EEG data and performed analysis on the structure of observed epochs and artefacts [**133**].

Principal component analysis used data reduction process in the analysis of EEG data. EEG data were recorded in streams of artefacts and epochs. EEG data principal component described the linear combination of optimally weighted observed EEG artefacts. The characteristic property of principal component analysis was that it considered the maximum number of total variance in the observed EEG artefacts. Due to the randomness of EEG data, solutions derived from principal component analysis can either be an orthogonal solution or an oblique solution. Orthogonal solution implied that EEG data components derived from principal component analysis remained uncorrelated. An oblique solution implied that EEG data derived from principal component analysis were correlated [**134**].

Given that EEG epochs are represented with p variables and n observed samples. The data were centred on the means of each observed epoch. This ensured the centring of the EEG data around the basis of the principal component without affecting the variances across the EEG data distribution or the spatial relationships on the EEG data [**135**]. The first EEG data principal component y_1, represented by the linear combination of each epoch, $x_1, x_2, \dots x_p$ was modelled as:

$$y_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1p}x_p \tag{5-11}$$

$$y_1 = a_1^T x \tag{5-12}$$

The first principal component was computed such that it took into consideration the highest possible variance in the EEG data set. The weights to the linear combination of each epoch were constrained such that the sum of their squares was unity.

$$a_{11}^2 + a_{12}^2 + \cdots + a_{1p}^2 = 1 \tag{5-13}$$

The second principal component was computed in the same way given that it was uncorrelated to the first principal component and that it accounted for the next highest EEG data variance [**134**].

$$y_2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{2p}x_p \tag{5-14}$$

The process continued until the total principal components were computed. The collective transformation of the original EEG data was modelled as [**135**]:

$$Y = AX \tag{5-15}$$

The process in which principal component analysis was conducted followed certain procedures as the governing rules to feature extraction. The number of initial components extracted during principal component analysis was equivalent to the number of EEG artefacts that was being analysed. The first component accounted for substantial amount of the data total variance. Each succeeding extracted EEG component accounted for progressively smaller expanse of the total variance. The number of important EEG components were determined and retained for rotation and interpretation. The number of significant EEG components was determined using the Kaiser criterion [**136**]. The "scree" test, accounted variance proportion, or the interpretability criterion.

The Kaiser criterion or the eigenvalue-one criterions allowed the retaining and interpretation of any EEG data component having an eigenvalue higher than one. Any EEG data component having an eigenvalue greater than one has accounted for substantial amount of the total variance than had been contributed by one EEG artefact. Such EEG artefact was retained as it accounted for significant amount of the total variance. With the "scree" test [**137**], the "break" between eigenvalues linked to each EEG data component was determined. The "break" distinguished between EEG components with relatively large eigenvalues and those with small eigenvalues. The EEG data components appearing before the "break" were considered to be important. They were retained for rotation and interpretation while the components appearing after the "break" were considered to be insignificant and were not retained [**138**]. The accounted variance proportion retained EEG components if they accounted for the specified percentage of the variance in the EEG data set. The variance proportion was computed as follows:

$$EEG\ Variance\ Proportion = \frac{Eigenvalue\ for\ the\ EEG\ component}{Total\ eigenvalues\ of\ the\ EEG\ data\ correlation\ matrix} \tag{5-16}$$

The total eigenvalues of the EEG data correlation matrix was equivalent to the total number EEG artefacts being analysed. Each EEG artefact contributed one unit of variance to the principal component analysis. The integrated interpretability criterion utilised a minimum of three retained EEG artefacts to determine if solution to the analysis was satisfactory. It also checked to see if the retained EEG artefacts shared the same theoretical meaning. The interpretability criterion also checked to determine if the retained artefacts were having different constructs in relevance to the analysis. Lastly, the interpretability criterion was used determine if the EEG component extraction patterns demonstrated or depicted the simple EEG signal structure. The EEG data matrix were rotated to final solution and interpreted. The interpretation of the rotated EEG artefact solution required that the weights of the retained EEG components be determined [**138**]. The use of principal component analysis on EEG data defined the orthogonal coordinate system used in the representation of EEG data. The orthogonal representation of EEG data ensured that EEG data were uncorrelated. PCA maximized the variance that occurred in each EEG epoch and observed data. The de-correlation of EEG data by PCA created the platform by which EEG artefacts were extracted and classified.

5.5.1 Differences Between PCA and LDA

Linear discriminant analysis maximized EEG class discrimination and differentiation while principal component analysis compressed EEG data variance into few components as much as possible. The linear discriminant analysis technique produced as many linear functions as the number of the required EEG data classes while the principal component analysis produced as many linear function as the raw EEG artefacts. Principal components analysis used data vectors which were uncorrelated and orthogonal to each other while the converse was the case for linear discriminant analysis [**139**].

5.6 Singular Value Decomposition (SVD)

Singular Value Decomposition (SVD) provided the ideal matrix factorization process. This provided solution to the least square problems [**140**]. The SVD condensed the maximum EEG signal energy into few coefficients. The SVD provided an effective EEG data splitting system into sets of linearly independent components required for EEG feature extraction and classification. Singular value decomposition technique factorized data on the basis of eigenvectors present in the data matrix [**141**].

Given that X represents $m \times n$ matrix of real-valued EEG data with rank r, where $m \geq n$ and $r \leq n$. The manifestation level for the ith EEG artefact in the jth EEG frequency class was given as x_{ij}. The components of the ith row of X formed the n-ddimensional vector g_i known as the transcriptional response of the ith EEG artefact. On the other hand, the component of the jth column of X formed the m-dimensional vector a_j known as the expression profile of the jth EEG frequency class [**142**]. The model for the singular value decomposition for the real valued EEG data is presented as:

$$X = USV^T \tag{5-17}$$

where U represents $m \times n$ matrix, S represents $n \times n$ diagonal matrix and V^T represents $n \times n$ matrix. The columns of U formed the orthonormal basis for the test data expression profiles and were termed left singular vectors $\{u_k\}$ such that $u_i \cdot u_j = 1$ for $i = j$ and $u_i \cdot u_j = 0$ for $i \neq j$. The rows of V^T formed the orthonormal basis for the EEG artefact transcriptional responses and were termed right singular vectors $\{v_k\}$. The non-zero S elements on the matrix diagonal are known as the singular values. Hence $S = diag\,(s_1, \dots \dots s_n)$; $s_k > 0$ for $1 \leq k \leq r$ and $s_i = 0$ for $(r+1) \leq k \leq n$. The collation of the data singular vectors was determined through high to low singular value arrangements with highest singular value at the upper left index of the S matrix. The solution derived from the discussed data extraction process was equivalent to diagonalization of the data matrix or eigenvalue matrix solution. The closest rank- l matrix to X is given as [**142**]:

$$X^l = \sum_{k=1}^{l} U_k S_k V^T \tag{5-18}$$

5.7 Wavelet Packet Transform (WPT)

The problem of EEG artefact identification for robotic control may be divided into two key stages namely EEG feature extraction and classification. These two elements appear to be independent while they are highly coupled. In order to create effective control commands from EEG artefacts. EEG feature extraction algorithm was modelled to have the capacity to separate the artefacts in the EEG data space. The classification algorithm was tuned to differentiate the different EEG classes in a given EEG feature space [**143**]. Wavelet packet transform provided more complex and flexible analysis algorithm for EEG signal thereby representing the generalized multi-resolution EEG signal decomposition. The wavelet packet algorithm decomposed both approximation components and detailed components for the analysis [**144**].

Filtering and de-noising EEG signals were important steps in the extraction and classification of EEG signals. EEG signals free from noise provided detailed information on human electrophysiology emanating from the brain. Creating and developing robot control commands from EEG signals required that the signals be clearly filtered and represented. Wavelet packet transform employed the threshold technique in filtering EEG signals. The threshold technique may be divided into two: hard threshold and soft threshold. The hard threshold technique discarded coefficients below the fixed threshold which are dependent on the EEG signal noise variance. The soft threshold technique discarded all coefficients and reduced coefficients that were above the fixed threshold [**145**].

The wavelet packet transform algorithm analysed EEG signals at different frequencies with different resolutions. The algorithm provided adequate time resolution with poor frequency resolution at high EEG frequencies. The algorithm also provided adequate frequency resolution with poor time resolution at low EEG frequencies [**146**]. Wavelet transform provided enormous number of small coefficients and small number of large coefficients. The large coefficients were the EEG signal values while the coefficients with lesser values were the noise elements of the EEG signal [**147**]. Wavelets can also be classified based on the orthogonality of the filter banks. The two classes are orthogonal wavelet filter banks and bi-orthogonal filter banks. The orthogonal wavelet filter have real coefficients that were of the same length and not symmetric. The bi-orthogonal wavelet filter had coefficients that were either real or integers. The bi-orthogonal low pass filter and high pass filters were not of the same length. The bi-orthogonal low pass filter was symmetric and the bi-orthogonal high pass filter can either be symmetric or unsymmetrical [**148**]. The wavelet high pass filter H_0 and the wavelet low pass filter G_0 have the following relationship:

$$H_0(z) = z^{-n} G_0(-z^{-1}) \tag{5-19}$$

The wavelet transform general signal processing process is shown in figure 5-2.

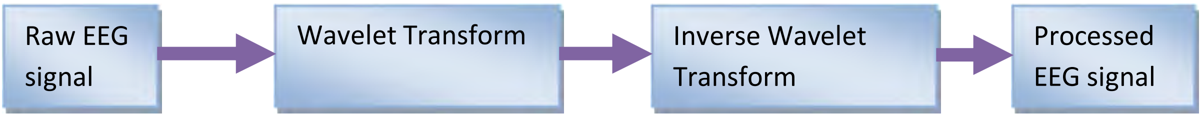


Figure 5-2: Wavelet Transform Signal Analysis Procedure

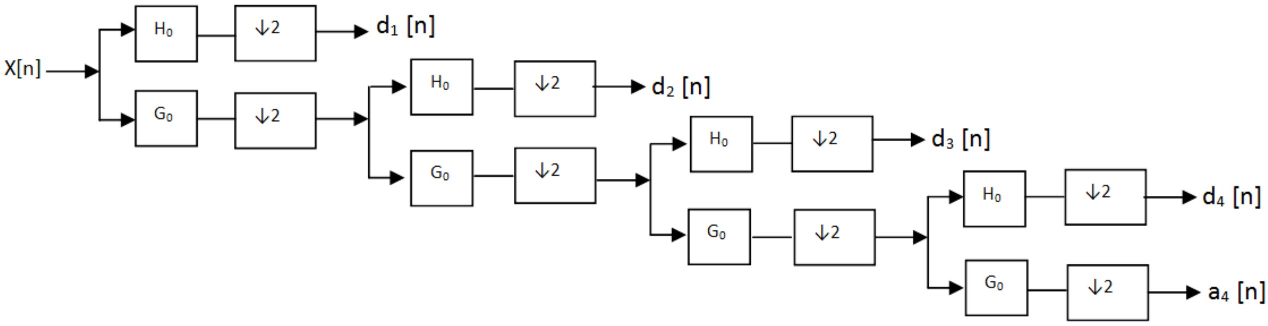


Figure 5-3: Four-Stage Wavelet Decomposition Tree

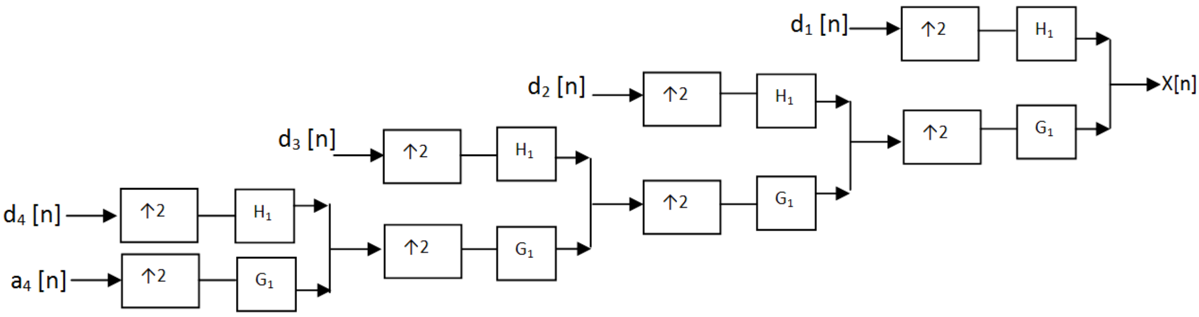


Figure 5-4: Four-Stage Wavelet Reconstruction Tree

5.8 Multilayer Perceptron

In the analysis of EEG signals, various forms of neural network algorithms were tested in the search for robust EEG artefact identification and classification algorithm. The Multiplayer Perceptron Neural Network (MLPNN) used the neural feed forward mechanism in the computational architecture assisted with back-propagation process. The architecture of the MLPNN was such that the algorithm studied the input mechanism of transformed EEG data under supervised neural network [**149**]. Multilayer perceptron neural network served as the indicative decision support system in the extraction and classification of EEG artefacts. Minimal loss of important data in the classification process was one of the integral objectives of the MLPNN. The MLPNN architecture provided the necessary tool required in modelling human brain activities. This facilitated the development of robots, human-machine interaction systems and brain-computer interfaces in assistive functions in real world applications [**150**]. Due to the dynamic nature of brain activities and EEG data, MLPNN were largely evaluated based on the availability and reliability of specific brainwaves. There were ranges of performance measures which were used in constraining the MLPNN. These performance measures include: EEG data accuracy, EEG data generalization, neural network reaction time, neural network priming and neural network speed-accuracy balance.

The perceptron neural network model played a crucial role in the detection and classification of EEG data and it used a linear activation function for the neural network activation. The perceptron model may be used to model a single biological neuron in the brain receiving numerous electric signals and neural firings. A single human neuron modelled with linear weighted function and threshold having $\underline{x} = (x_1, x_2, x_3, \dots, x_n)$ as inputs from several neural firings in the brain was presented as an EEG feature vector in n-dimensional EEG feature space.

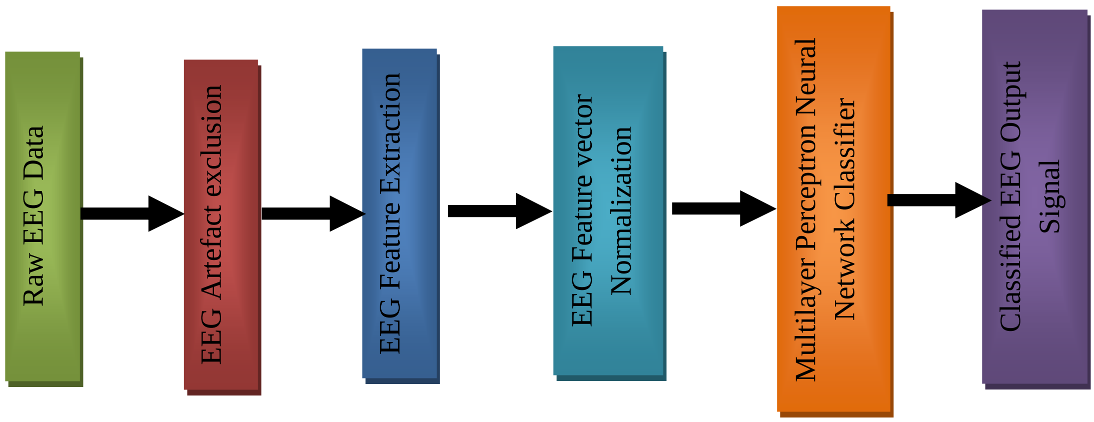


Figure 5-5: EEG Data Classification Process Using MLPNN

The net function $u(\underline{x})$ represents the weighted sum of the neural firings received by a neuron in the brain.

$$u(\underline{x}) = w_0 + \sum_{i=1}^{n} w_i x_i \tag{5-20}$$

The output from the perceptron model $y(\underline{x})$ obtained from the net function through the threshold activation function is presented as:

$$y(\underline{x}) = \begin{cases} 1 & u(\underline{x}) \geq 0 \\ 0 & u(\underline{x}) < 0 \end{cases} \tag{5-21}$$

The perceptron has some drawbacks in real world applications. Nonlinear transformation required for appropriate EEG feature extraction was not specified. In an event where the EEG feature patterns were not linearly separable, the perceptron learning algorithm failed to converge. This was the case where the expressive, affective and cognitive states of the brain were active. There were cases where only the expressive EEG features were present and linearly separable. In such cases, information on how long it took the algorithm to converge to a weight vector corresponding to the hyper-plane separating EEG features was not known. In using the perceptron neuron model for EEG data detection and classification, the EEG input feature vector $\underline{x}$ was closely matched with the weight vector $\underline{w} = (w_1, w_2, w_3, \dots, w_n)$ such that the inner product of the EEG input feature and the weight vector exceeded the specified threshold $-w_0$. This then implied that the output signal indicated as $+1$ represented the detection of the target EEG signal. To determine the weight vector $\underline{w}$ suitable for the perceptron algorithm, an iterative algorithm expressed in equation (5-22) estimated the right value of $\underline{w}$. This was done by using EEG sample data presented in a random sequential order to the perceptron neuron model.

$$\underline{w}(k+1) = \underline{w}(k) + \eta(d(k) - y(k))\underline{x}(k) \tag{5-22}$$

Where $\underline{x}(k)$ represents the training samples $y(k)$ represents the output and the index k indicates the sequential application of the samples to the perceptron in random order. The Multilayer Perceptron (MLP) neural network model consists of feed-forward, layered network of McCulloch and Pitts' neuron. The neurons in the MLP network have nonlinear activation function that was continuously differentiable. The MLP provided nonlinear mapping between EEG data input and output [**82**]. The weighted values for the MLP network were found through error back-propagation training technique. For a set of EEG training data sample $[(\boldsymbol{x}(k), d(k));\ \ 1 \leq k \leq K]$ and weight matrix $\boldsymbol{W}$ the error back-propagation training included all K inputs through the MLP network. This allowed the computation of the corresponding output $\{z(k); 1 \leq k \leq K\}$. The error $E$is computed as

$$E = \sum_{k=1}^{K}[e(k)]^2 = \sum_{k=1}^{K}[d(k) - z(k)]^2 \sum_{k=1}^{K}[d(k) - f(\boldsymbol{W}\boldsymbol{x}(k))]^2 \tag{5-23}$$

The objective of the iterative process was to adjust the weight matrix such that the error E is minimised. This introduced nonlinear least square optimisation methods for neural network weight computation. The iterative process utilised the following process:

$$\boldsymbol{W}(t+1) = \boldsymbol{W}(t) + \Delta\boldsymbol{W}(t) \tag{5-24}$$

Where $\Delta\boldsymbol{W}(t)$ represents the corrections made to current EEG data weights $\boldsymbol{W}(t)$.

In table F-1 in the appendix section, iterative nonlinear optimisation algorithms capable of resolving MLP weights are presented.

5.9 Learning Vector Quantisation (LVQ) Neural Network

Learning Vector Quantisation is the classical EEG signal approximation technique employed in the quantised approximation of EEG data distribution. Various brainwaves were used as input vectors in supervised learning algorithm [**151**]. In the implementation of stochastic EEG input data vectors $x \in \mathcal{R}^n$, having the probability density function $p(x)$, codebook vectors $m_i \in \mathcal{R}^n$, $i = 1,2,3,\dots,k$ required that the approximation process of the input vectors finds the closest codebook vector m_c to x within the defined input space[24] in the Euclidean metric [**152**]. The quantisation of EEG data is presented as:

$$\|x - m_c\| = \min_i \|x - m_i\| \tag{5-25}$$

and the quantisation error E for the EEG data representing the distortion measure for the EEG data is given as:

$$E = \int \|x - m_c\|^2 \, p(x) dx \tag{5-26}$$

In considering the above equations, the minimisation of the quantisation error by m_i reflected the average quantisation error for each EEG Voronoi set[25] [**152**].

In the implementation of learning vector quantisation on EEG data, the algorithm used competitive learning neural net function with supervision for EEG pattern classification [**153**]. The training set consisted of training vectors, target outputs and M classes smaller than the training vectors is represented as:

$$\{S^{(q)} : t^{(q)}\}, \; q = 1,2,3,\dots,Q$$

$$t_i^{(q)} = \begin{cases} 1, & \mathit{if}\ S^{(q)} \mathit{belongs\ to\ class\ i} \\ 0, & \mathit{otherwise} \end{cases} \tag{5-27}$$

where Q represents the training vectors, $t^{(q)}$ represents M dimensional target outputs, $S^{(q)}$ represents N dimensional training vectors [**153**]

5.10 Bayesian Paradigm in EEG Analysis

Consider the situations where the noise signals from the environment are present in brainwaves and are detectable. The conditions of the environment where the individual operates and functions might be of

[24] The input space in this case refers to the number of the available brainwave signal

[25] x Vectors having specific reference vector as their closest neighbor and in the corresponding Voronoi tessellation partition constitute Voronoi set. Voronois tessellation is the indication of reference vectors to their corresponding mid-planes or partitions

concern as it might introduce signal interferences. Given that biological signals may be unbiased, the combination of cognitive information from an individual may be suitable for the neural network to adapt and learn the true fundamental state of brainwaves. The question can be formulated as "what type of physiological behaviours, movements, cognitive activities and cognitive load will be sufficient to produce data aggregation in the brainwaves". The natural yardstick in the identification of brainwaves having conclusive cognitive information from an individual sufficient for information aggregation could be expressed through the large number argument law. The use of large number argument law may fail in the light of information exactness. The introduction of Bayesian dynamic philosophy and the balance between cognitive signal identification and useful biological signal implementation brings together sequential actions through EEG signal observations [**154**].

5.10.1 The EEG Bayesian Search Paradigm

Search theory has been applied to various researches in operation management problems. Operation research problems have targets and searching mechanisms as the common elements existing in these problems [**155**]. Implementing and applying Bayesian characteristics in the extraction of EEG artefacts made the problem of artefact search to be a search theory problem. Search theory provided the analytical resource tool for feature allocation in EEG signal frequency space [**156**]. This subsection discussed the Bayesian search theory in EEG data analysis.

The adaptation of search theory in EEG artefact search and selection was aimed at improving efficiency in the EEG signal and extraction mechanisms. In the adaptation of search theory, mechanism of particular interest was referred to as directed search in this study. Directed search allowed the neural network to use EEG signal frequencies to directly affect the EEG artefact matching frequency. Directed search enabled the neural networks to efficiently allocate and classify EEG artefacts within the bounds of the matching technology.

The EEG artefact search theory can be summarised as follows:

- The EEG artefacts are contained within vast biological frequencies. The frequencies are too large for search mechanisms to search and identify completely in the human brain.
- The locality of the artefact was not known exactly, but probabilities were associated with brain lobes as sub regions of the brain.
- EEG artefacts may or may not be generated.
- One or more electrodes may be used to look for the EEG artefact.

In order to find solution to the EEG artefact search theory, the following was required:

- Initial density model was required to locate the site of the EEG artefact at the beginning of the search.

- The model to identify EEG artefact generation event and the event was represented by $q(x, y, t)$.
- The minimization of the time required to detect an artefact or maximizing the probability of detection through time serving as the mathematical objective function for the model.

5.10.2 Random EEG Artefact Matching and Inefficiency

The brain generates large number of neural signals. Considering the EEG signal acquiring system consisting of many EEG electrodes and neural firings. The number of electrodes searching for or placed at a neural firing site has a fixed value u. All the electrodes were made from the same material and have neutral risk factor. When placed on the scalp, the electrodes detected EEG signals whose value was $y > 0$. When the EEG electrodes were removed from the scalp, their utility was normalised to zero. The number of available sites for EEG signal acquisition was given by v. The probable event that an individual may incur loss of energy and concentration c in generation EEG signal were bounded by $0 < c < y$. The quality of technology employed in the acquisition of EEG signal has constant returns and was normalised to zero [**156**].

In describing the complete number of matches for the given EEG signal time series, $M(u, v)$, was used as the matching function. Let $\theta = u/v$ represents the "tightness"[26] of the EEG signal. The matching probability for the artefact acquisition using the electrodes are $p(\theta) = M(u, v)/u$ and the matching probability for the availability of active neural sites are $q(\theta) = M(u.v)/v$. Given the assumption that M was an increasing, differentiable and concave function in each model for all θ it followed that $p, q \in (0,1)$ provided the necessary boundary conditions. The characteristic property of M was such that it had a constant return to scale making $p(\theta)$ to decrease in θ and $q(\theta)$ increase in θ such that $q(\theta) = \theta p(\theta)$. It was also assumed that the output of $q(\theta)$ was concave and $q(0) = 0;\ \ q(\infty) = 1$. The EEG artefact electrode matching to neural sites is modelled as:

$$s(\theta) = \frac{u}{M} \frac{\partial M(u,v)}{\partial u} \tag{5-28}$$

And

$$s(\theta) = 1 + \theta p'(\theta)/p \tag{5-29}$$

The matching of the availability of neural sites is $(1 - s)$. Once the artefact and the available neural site are matched, the physiological or cognitive activity, w responsible for neural firings at the neural site is chosen. The choice criteria were made available using Nash bargaining technique as it maximized geometrically the weighted extras of the artefact and the neural site [**156**]. $w^{\sigma}(y - w)^{1-\sigma}$ and the bargaining weight was bounded by $\sigma \in [0,1]$. The result for the physiological and cognitive activity

[26] Tightness refers to the closeness and overlapping properties of EEG signal frequencies and signal bands

share was given by $\frac{w}{y} = \sigma$. The expected artefact value was $J = q\big(\theta(w)\big)(y - w)$ and the value for search process given by $V = p(\theta)w$. The equilibrium condition in matching EEG artefact randomly is given by $(1 - \sigma)q(\theta) = c/y$. The unique result for θ exists within $0 < c < (1 - \sigma)y$.

5.10.3 Directed Search and Artefact Detection Efficiency

Directed search connected brainwave frequency bands to the matching EEG artefact frequency profiles. This was done through EEG signal explicit modelling between the brainwave frequency bands and the matching EEG artefact frequency. To apprehend the concept, suppose all EEG artefacts were expected to be associated with EEG frequencies by the function $\theta(w)$. EEG Artefact search was directed such that the identification of a particular EEG frequency changes the EEG artefact matching probability by affecting the EEG signal detection process. For the cognitive and physiological activities that generate EEG signals w , the matching probability is given as: $q\big(\theta(w)\big)$; for the artefact identification technique employed in the analysis of EEG signal w , the matching probability is given as: $p\big(\theta(w)\big)$. The tightness function for the artefact search process provided the means to maximize the expected artefact value $J = q\big(\theta(w)\big)(y - w)$ given that each physiological and cognitive activity generated EEG signals that maximized the expected value $V = p\big(\theta(w)\big)w$. The EEG signal equilibrium tightness was made consistent with physiological activities and the artefact search process decisions [**156**]. Directed search was developed to allow EEG artefact extraction algorithms to explicitly make trade-offs between EEG frequency bands and the possible artefact classes. Directed search was aimed at restoring efficiencies lacked by other classification techniques. Efficient classification of EEG artefacts by the directed search algorithm may not utilise full computational resources due to matching technology constraints.

5.10.4 The Bayesian Brain Model

In the estimation, extraction and classification of EEG signals; neural coding was an important aspect of EEG signal modelling and analysis. To further provide insight into neural coding and its functions in the analysis of EEG signal, Bayesian paradigm was employed to better appreciate the role of statistical tools in EEG signal classification, decision-making and control applications [**157**]. This section showcased the influence of Bayes model on the performance of artificial neural network designed to manage the extraction and classification of EEG signals. There were significant associations between the use of statistical tools and neural network modelling. There was cross-fertilization in the implementation of the methodologies in the EEG signal analysis [**158**].

5.10.5 Maximum Likelihood and Bayes Brain

The design of an optimal classifier was possible provided that there was prior information $p(\omega_i)$ on the factors influencing EEG artefact classification conditional densities $p(x|\omega_i)$. Often in real world applications it was seldom to find complete information on the probability structure of pattern recognition problems. The characteristic pattern recognition cases required some imprecise data structure merged with observed data and training data representing the data patterns in question. Observed EEG data samples were used to estimate the unknown probabilities and probability densities. In classical supervised EEG classification problems, prior probability estimation poses no problem to the classification of data [**159**]. This section discussed the maximum likelihood parameter estimation and the Bayesian estimation. Considering the EEG artefact class conditional density $p(x|\omega_i)$ having normal density profile, mean μ and covariance matrix $\sum_i$; the estimation of the artefact class conditional density shifts to the estimation of the mean and covariance matrix and this simplified the EEG artefact classification problem. Parameter estimation for the EEG data classification was achieved through various methods. Suppose EEG frequencies are data samples group into classes. The sets c derived from the EEG frequency classes, $D_1, \ldots, D_c$ drawn independently with recorded EEG data samples in D_i in accordance to the probability rule $p(x|\omega_i)$. The EEG data samples were regarded as independent identical distributed random variables. To estimate the parametric factor for the Bayes brain model, $p(x|\omega_i)$ was assumed to have a known parametric form determined by the unique parametric vector θ_i, where θ_i contained components of the covariance matrix $\sum_i$ and the mean μ. The objective of this process was to utilize information derived from the EEG data samples to generate good estimates for the unknown parameter vectors $\theta_1, \ldots, \theta_c$ linked to each EEG data frequency [**159**]. Considering the case where there are n recorded EEG data samples, $x_1, \ldots, x_n$ drawn were independently. The likelihood of the unknown parameter θ associated to the recorded EEG data samples was given as:

$$p(D|\theta) = p(x_k|\theta) \quad (5\text{-}30)$$

The maximum likelihood estimate of the unknown parameter θ, was given by the value of θ that maximizes $p(D|\theta)$ [**159**].

5.10.6 Bayes Neural Network Model

Considering infinite number of neural firing sites on the scalp associated with EEG electrodes, indexed by $n \in \mathbb{N}$, and randomly firing in response to cognitive processes are possibly linked by a single EEG electrode. The success of an electrode in sensing each firing depends on the basic cognitive state of an individual θ and his thought processes. Assuming the cognitive state of the individual and the thought process are binary. The thought process of associated to cognitive process and linked to electrode n is represented by $x_n \in \{0,1\}$ and the principal cognitive state is denoted by $\theta \in \{0, 1\}$. The success of electrode n in capturing the neural firings is presented as:

$$u_n(x_n, \theta) = \begin{cases} 1 & if\ x_n = \theta \\ 0 & if\ x_n \neq \theta \end{cases} \quad (5\text{-}31)$$

Both values of the cognitive state in the above expression are assumed to be similar so as to simply symbolization, hence $\mathrm{P}(\theta = 0) = \mathrm{P}(\theta = 1) = 0.5$.

Given that the principal cognitive state of an individual was dynamic and assumed to be unknown, each neural firing linked to EEG electrode $n \in \mathbb{N}$ forms the cognitive processes describing the current cognitive state of the individual from the EEG signal $s_n \in S$; where S represents the Euclidean space for the human scalp and signal source. EEG signal are independently generated in accordance to the probability measure F_θ of the signal irrespective of the conditional cognitive state of an individual. The EEG signal structure construct measures for the Bayes model was denoted by$(\mathrm{F}_0, \mathrm{F}_1)$. In the model, F_0 and F_1 were assumed to be continuous relative to each other and this implied that no single EEG signal has the full revelation on the principal cognitive state of an individual. The second assumption made on the signal structure constructs was that F_0 and F_1 are not identical. This assumption allowed for relevant information to be embedded and carried by each of the EEG signal.

In contrast to traditional neural network learning strategies, the electrodes were assumed to not observe and measure all the firings from the neural sites and prior neural firings. Rather the electrodes observed and measured EEG firings within their radius in accordance to the structure of the neural network. Each neural firing linked to an electrode observes the neural activity of other neural sites stochastically generated in its neighbourhood represented by $B(n)$[27]. Given that EEG electrodes can only observe signals as they are generated $B(n) \subseteq \{1,2,\dots,n-1\}$. Each neural site and firing neighbourhood $B(n)$ was constructed in accordance to random probability distribution $\mathbb{Q}_n$ over the set of all subsets of $\{1,2,\dots,n-1\}$. The sequence of $\{\mathbb{Q}_n\}_{n\in N}$ generated from sets of EEG data for each $\mathbb{Q}_n$ are independent of each other for all n as observed in each EEG signals. The sequence of $\{\mathbb{Q}_n\}_{n\in N}$ distribution formed the EEG Bayes neural network structure created by the combinations of neural firings and recording EEG electrodes. $\{\mathbb{Q}_n\}_{n\in N}$ expressed deterministic EEG neural networks structure given that the probability distribution of $\mathbb{Q}_n$ represented Dirac[28] distribution for all n else if $\mathbb{Q}_n$ was non-Dirac, then $\{\mathbb{Q}_n\}_{n\in N}$ represented a stochastic EEG neural network. The EEG Bayes neural network structure consisted of the neural network structure $\{\mathbb{Q}_n\}_{n\in N}$ and EEG signal structure $(\mathrm{F}_0, \mathrm{F}_1)$.

5.10.7 Bayesian Learning in EEG Neural Networks

This section discusses and presents Bayesian learning in EEG neural networks. Each electrode on the human scalp received EEG signals. The EEG signals represented the principal cognitive state of the human brain with the observation of stochastic neighbouring neuronal signals. There are two possible decisions that can be selected in Bayesian algorithm. The characterisation of pure stabilization strategy for stochastic and deterministic EEG neural network and the characterization of the conditions which provide asymptotic learning in the EEG neural network are the possible decisions. The conditions for asymptotic learning generally provided tools that aided the selection of the right decision as individual

[27] EEG electrode linked to neural firing n observes not only the neural activity of n', it also takes cognizance of the characteristic property of the neural firing n' given that $n' \in B(n)$

[28] Implies de-generation of network distribution

EEG signals were classified towards a specific artefact or signal group. The individual cognitive processes were unbounded. This implied that likelihood ratios[29] were unbounded. There was asymptotic learning provided there was minimum EEG signal generation. The main contribution and proposition in this section showed that given the probability of each EEG signal recording, prior EEG observations in conjunction with current observation converged to unity as the EEG neural network increased. This provided unbounded individual cognitive processes sufficient edge to ensure asymptotic learning. The proposition established that with unbounded individual cognitive processes, there was asymptotic learning in the EEG neural network. In disparity to peculiar situations where prior cognitive processes were observed, asymptotic learning was possible even with bounded cognitive processes [**154**]

Considering the case where bio-signal generated from human cognitive processes were dispersed and decentralized; the condition in which bio-signals representing the cognitive state of an individual have noise components to their properties. If EEG signals were unbiased, the combination of individual EEG signals provided sufficient information about an individual cognitive process. The information was provided with the aim of learning the true intents and action for neuronal signals. The question on cognitive convergence was formulated as the investigation of what categories of cognitive activities and communication arrangements led to the required type of EEG signal combinations. In applying Condorcet's Jury theorem [**160**], accurate recording of each cognitive process provided adequate combinatory EEG data by the law of large numbers argument [**161**]

Starting with recognized principles of sequential learning problem, except that instead of using full prior EEG observations, general neural network topology was assumed. With large number of EEG electrodes transmitting EEG signals more specifically decisions were made in choosing between two EEG artefacts. An essential cognitive state determined the success of these two actions or choices. Each electrode received a neuronal signal on which these two choices yielded a higher success. Preferences in choices any of the signals from the electrodes were aligned such that the basic cognitive state of the individual was well represented. The process was characterized by two structures: (1) the EEG signal structure, which determined the type of information carried by the signal or the type of cognitive actions associated with the EEG signal; (2) the EEG neural network structure, which determined how EEG signals associated with a cognitive process were transmitted in the neural network. The EEG neural network was modelled as a stochastic process that determined the individual EEG electrode placement neighbourhood. Each EEG electrode observed past prior cognitive processes in its neighbourhood. Driven by the neural network construal, throughout the thesis, it was assumed that the EEG electrodes were identical and has the capacity to observe and distinguish cognitive processes from the

[29] The likelihood ratio refers to the ratio of the probabilities or densities of EEG signal generated as a result of a specific cognitive state relative to another cognitive state [**154**]

neighbouring electrode. The realisations of electrode neighbourhood properties as well as individual electrode properties were regarded as peculiar information specific to that electrode.

In considering the stochastic process of generating EEG electrode neighbourhoods in the EEG neural network structure, it was critical to differentiate between deterministic and stochastic network structures. In the deterministic network structure, there were no uncertainties with regards to the neighbourhood of each EEG electrode and the information contained the neighbourhoods were common knowledge. In the stochastic network structure there were uncertainties in the neighbourhoods of the EEG electrodes [**154**]. In providing logical characterization for the conditions suitable for stabilization of information combination in EEG neural networks, it was proposed that there exists information combination or asymptotic learning given that, in the limit, as the size of the EEG neural network was subjectively large, individual cognitive processes converged to the actions that generated the EEG signal. This yielded a higher success rate in the classification of EEG artefact. It was also proposed that there was failure in asymptotic learning if the EEG network was large and the right action was not associated with the cognitive process responsible for the EEG signal.

In presenting two critical ideas in the stabilization of information transmitted by EEG neural network, cognitive process and thought process were regarded as bounded properties of EEG data. The first concept expressed the likelihood ratio of the individual EEG signals as finite and bounded away from zero. Cognitive and thought processes that satisfied this condition were regarded as bounded cognitive and thought processes. In bounded cognitive and thought process there were maximum numbers of data that was carried by any of the EEG signals [**162**] in relation to the cognitive state at hand. In distinguishing between the concepts of likelihood ratios, there were EEG signals having random high and low likelihood ratios. This represented cognitive processes that were unbounded. The proving of better approximations in reality through bounded and unbounded cognitive processes was partly an empirical question that was influenced by interpretational conclusions from different EEG recordings.

The second concept drew its principles from the construct that neural network structure allowed for expansion. The new network nodes could be added to aid the transmission of large information from the human brain. In explaining this concept, the idea of finite number of EEG electrodes was introduced. The finite number of EEG electrode was significant given that there was infinite number of neural firings associated to infinite number of possible electrodes with their probability homogeneously bounded away from zero while observing only the subset of this cluster [**154**]. For instance, an EEG data cluster was significantly influential if it was the basis of all information derived from the EEG data except for the individual EEG signals for an infinitely large neural network as the human brain and nervous system. If there are significantly influential cluster of EEG data, then the neural network has nonexpanding cognitive processes generating EEG data and contrariwise. If there existed no significant influential EEG data cluster, the neural network has expanding cognitive processes generating EEG data. The core results derived from the Bayes paradigm in the subsection are summarized as follows:

Result One: The first result showed that there was no asymptotic learning in EEG neural network with non-expanding EEG recordings. This was true, since information combination was not possible given that EEG recordings from infinite group of different individuals may develop decision sets from the EEG data and remain limited in their application.

Result Two: The second result indicated that individual cognitive processes were unbounded and EEG neural network structure expanded with new information. There was asymptotic learning due to the unbounded nature of the cognitive processes. This result was useful while considering unbounded cognitive processes as better approximations for real life applications than bounded cognitive processes. This result implied that given the case where there was information saturation as a result of data from neighbouring EEG electrodes learning may be relaxed for a while. Asymptotic learning still continues given that the cognitive processes are still unbounded.

Result Three: This result showed that in deterministic and stochastic EEG neural network, bounded cognitive processes were mismatched with asymptotic learning. The findings were based on generalisations of asymptotic learning.

Result Four: This result showed that with bounded cognitive processes, asymptotic learning was still possible in certain stochastic EEG neural network structure. In this scenario, there were sufficient arrival of new cognitive data as decisions was made with limited information especially in the classification and extraction of EEG artefacts. The consequence of this result was that bounded cognitive processes could combine and lead to asymptotic learning in the EEG neural network. This result was of significance as it showed how simple EEG neural network structure stabilization was affected.

5.11 Logistic Regression as the Classifier

In the classification of EEG artefacts for use in robot control strategy development, it was imperative that a predictive algorithm was used to ascertain and determine the existence of the EEG artefact of interest before it can be further used [**163**]. Logistic regression provided the necessary algorithm for predicting the dichotomous outcome of EEG artefact classification process. Errors which were evident in the logistic regression algorithm followed the logistic distribution against it being normally distributed. The Logistic regression algorithm was efficient in determining the outcome of two possible solutions [**164**]. For example if the robot control strategy was specified and designed to use EEG artefact derived from blinking the eye, the logistic algorithm filtered the data and determined the presence or absence of the blinking eye EEG artefact. In the midst of other EEG artefacts, logistic regression served to determine the impact of several independent EEG artefacts appearing simultaneously within the control strategy towards the prediction of other dependent EEG artefacts.

The conditional response of the EEG artefact classification algorithm given that the EEG input data represented as $\Pr(Y|X)$ provided insights on the preciseness of the artefact prediction algorithm. In modelling the logistic regression classification algorithm, let "1" and "0" be two distinct binary classes. "1" was defined as the presence or occurrence of EEG artefact of interest and "0" was defined as the absence of the EEG artefact of interest or occurrence of other EEG artefacts. In the probabilistic distribution of EEG artefacts, "Y" was defined as the indicator variable for the EEG artefact of interest and "X" was defined as the non-indicator variable. The proposition that $\Pr(Y = 1) = E[Y]$ and $\Pr(Y = 1|X = x) = E[Y|X = x]$. This implied that the conditional probability of EEG artefact of interest occurrence was the conditional expectation of the indicator variable [**165**]. In order to ensure that the logistic regression algorithm efficiently executed specified functions and objectives, a smoothing function was integrated into the algorithm. This ensured that the indicator variable was not in conflict with the conditional probability function. Given that $\Pr(Y = 1|X =) = p(x; \theta)$ for the EEG artefact classification function parameterized by θ within the premise that recorded neural activities were independent of each other. The conditional likelihood function for the classification function is presented as:

$$\prod_{i=1}^{n} \Pr(Y = y_i|X = x_i) = \prod_{i=1}^{n} p(x_i; \theta)^{y_i}(1 - p(x_i; \theta)^{1-y_i} \tag{5-31}$$

Given that the recording of EEG data may be carried out in the sequence of trials and sequence of tasks, it was worthy to note that for trials $y_1, \dots, y_n$ in the event that there was constant probability of success$p$, the likelihood that an EEG artefact of interest would be classified was given as:

$$\prod_{i=1}^{n} p^{y_i} (1 - p)^{1-y_i} \tag{5-32}$$

The likelihood to classify EEG artefact of interest was maximized given that

$$p = \hat{p} = n^{-1} \sum_{i=1}^{n} y_i \tag{5-33}$$

In the event that in each of the EEG recordings there was a success in classifying the artefact of interest p_i, the likelihood for the classification process became

$$\prod_{i=1}^{n} p_i^{y_i} (1 - p_i)^{1-y_i} \tag{5-34}$$

In order to ensure that the inhomogeneous behaviour of the Bernoulli model embedded in the maximum likelihood classification function was robust in the classification process; the assumption that p_i was not an arbitrary number was made such that when ever p_i was true, $x_i$was true with similar values

[165]. In considering the possibility of the preliminary models of p, the logistic regression algorithm for classifying EEG artefact with no ambiguity in the results was given as:

$$\ln \frac{p(x)}{1-p(x)} = \beta_0 + x \cdot \beta \tag{5-35}$$

and

$$p(x) = \frac{e^{\beta_0 + x \cdot \beta}}{1+e^{\beta_0 + x \cdot \beta}} = \frac{1}{1+e^{-(\beta_0 + x \cdot \beta)}} \tag{5-36}$$

where $p(x)$ represents the probability of classifying the EEG artefact of interest, β represents the regression coefficient and x represents y-axis intercept [166]. The implication of this result was that the artefact classification prediction was successful provided that $Y = 1$ given that $p \geq 0.5$ and $Y = 0$ given that $p < 0.5$. The logistic regression algorithm provided useful linear classifier which was suitable in classifying artefacts of interest in recorded EEG data. The decision rule in separating artefacts of interest was based on the solution derived from $\beta_0 + x \cdot \beta = 0$. Another deduction from the logistic regression model provided boundaries for the classification of the EEG artefacts. The probability of classifying the artefact of interest was dependent on the distance from the artefact classification boundary.

The logistic regression model for EEG artefact classification worked well when there was the need to have more than two classes of artefacts. For the case where more than two artefact classifications were required for instance k classes. This implied that Y the prediction classification model can take more than two values. For more than two classifications, offsets were introduced for each EEG frequency data. Given β_0, β parameters for each artefact class c in $0{:}\,(k-1)$ has the offset $\beta_0^{(c)}$ and vector $\beta^{(c)}$. The conditional probability prediction for the artefact classification is presented as:

$$\Pr\left(Y = c \middle| \vec{X} = x\right) = \frac{e^{\beta_0^{(c)} + x \cdot \beta^{(c)}}}{\sum_c e^{\beta_0^{(c)} + x \cdot \beta^{(c)}}} \tag{5-37}$$

For any number of possible artefact classification, parameters may be fixed at zero with losing the conditions for generalising the model. The implication of this was that the parameters were chosen arbitrarily to zero out frequencies which are not of interest in the classification. This was done without affecting the predicted probability for the classification the class in question. The different parameter specifications yielded the same result. In order to ascertain the effectiveness of the algorithm, the first artefact class parameters were zeroed out. The parameters for other artefact classes existing within the recorded EEG data were estimated efficiently [165]. The model for classifying more two EEG artefacts is given as:

$$\ln \frac{P(x)}{1-p(x)} = \beta_0 + x_1\beta_1 + x_2\beta_2 +, \ldots . + x_n\beta_n \tag{5-38}$$

and

$$P(x) = \frac{e^{\beta_0 + x_1\beta_1 + x_2\beta_2 +, \ldots + x_n\beta_n}}{1 + e^{\beta_0 + x_1\beta_1 + x_2\beta_2 +, \ldots + x_n\beta_n}} \tag{5-39}$$

5.12 Finite Impulse Response Filter in Neural Network

The technique which was viable in the analysis of EEG signal for feature extraction was the use of finite impulse response (FIR) filters. The FIR filter computed EEG signal out as weighted finite sum of raw EEG signal as inputs into the filter. The FIR filter was centred on the feed-forward principle of feed-forward neural networks. The FIR filter provided robustness for neural networks used in the analysis of EEG signal through computational efficiency in both recursive and non-recursive neural network realization. The FIR filter has minimal noise output from computational errors and sensitivity to variation in filter coefficients are minimal [**167**]. The FIR filter is presented as [**168**]:

$$y[n] = \sum_{k=0}^{N-1} b_k \cdot x[n-k] \tag{5-40}$$

Where $y[n]$ denotes the FIR filter output, b_k denotes the FIR filter coefficients, N represents the number of FIR filter coefficients required in EEG signal analysis and $x[n]$ represents input to the FIR filter from raw EEG signal. The FIR filter specification is given as [**168**]:

$$x[n-k] = \begin{cases} 1 & for\, n = k \\ 0 & for\, n \neq k \end{cases} \tag{5-41}$$

5.13 Proposed EEG Extraction and Classification Model

The critical processes that were considered in the development of modular and robust BCI system included EEG feature extraction and classification. FIR filter and multi-layer perceptron were used to model the relation that existed between motor cortical neural firing and hand movements [**169**]. The classification of brainwave involved the transformation of electrophysiological inputs from subjects into robotic control commands which was the integral component of BCI systems. EEG signal classifiers are regarded as “weak” as the result of the following conditions [**170**]:

1. If incorrect model assumption was made during the development of the classifier,
2. If the classification rule has a low complexity and technique required to solve the problem on hand,
3. If there are incorrect classifier settings or estimations for classifier parameters,
4. If the classifier is unstable.

EEG signal energy distribution has scattered energy distribution profile around the scalp. EEG signal features are hidden in the noise that accompanies the signal. The extraction of EEG signal required that the signal analysis provide accurate description of the signal distribution as the function of time and frequency. Discrete Fast Fourier Transform (FFT) has proven to be the technique suitable for use in the representation of EEG signal spectrum. The application of short time Fast Fourier Transform to stationary EEG spectrum allowed for piecewise approximation of EEG signals for classification and analysis [**171**]. Using visual inspection of multiple time series of EEG signals in their raw form was still the predominant technique used for the identification and classification of EEG patterns especially in the medical community [**172**]. The first step towards the classification of EEG signals was to identify an adequate classifier for the EEG signal that satisfied the following conditions:

- The classification paradigm should be used in context for signal and pattern recognition.
- The process should have the capacity to ascertain what the BCI system is learning.
- The classification process should be such that minimal numbers of arithmetic operations are implemented.

In EEG feature extraction, S1 discussed in subsection 2.8.9 provided an adequate marker for the EEG signal. This was due to its high energy and lower morphologic variability in comparison to other segments of the EEG signal. At the detection of each S1, the time series of EEG signal was estimated by measuring the time interval between each S1 [**173**]. The simplified process shown in figure 5-6 used the S1 identifier sequence for S2 identification during EEG signal filtering [**174**].

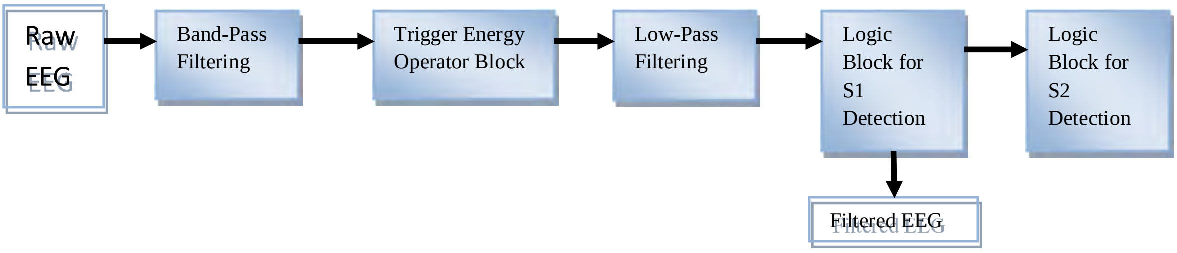


Figure 5-6: Block Diagram of Raw EEG Filtering

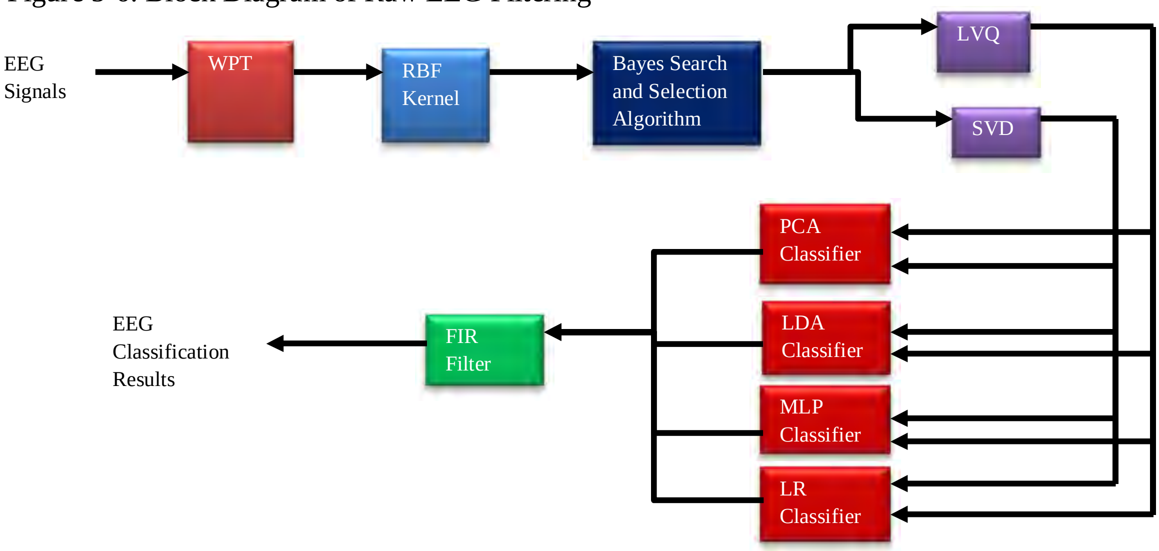


Figure 5-7: Schematic Illustration of Proposed Augmentation Model

5.14 Simulation Results and Implications

This section presents the results and findings realised from the chapter. The results showcase the findings from the subsystems shown in figure 5-7. The implications of the results are presented also in each subsection.

5.14.1 Time Frequency Analysis

Time frequency analysis was used to validate EEG signal decomposition through the signal power spectrum. The red lines in the figure represent imaginary values and the blue lines represent real values. In figure 5-8 the power measure and EEG spectral power are shown. Event-related activities and changes were monitored through time frequency analysis of EEG signals. Figure 5-9 illustrates the integration of the brain cortex as the source of EEG signals and the head model in time frequency.

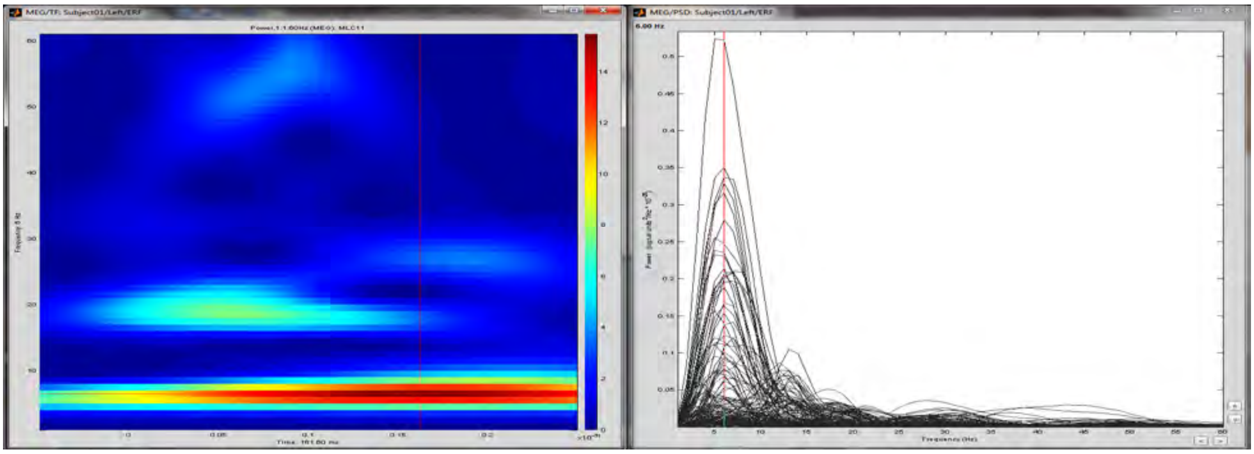


Figure 5-8: Power Measure and Power Spectrum for the EEG Data

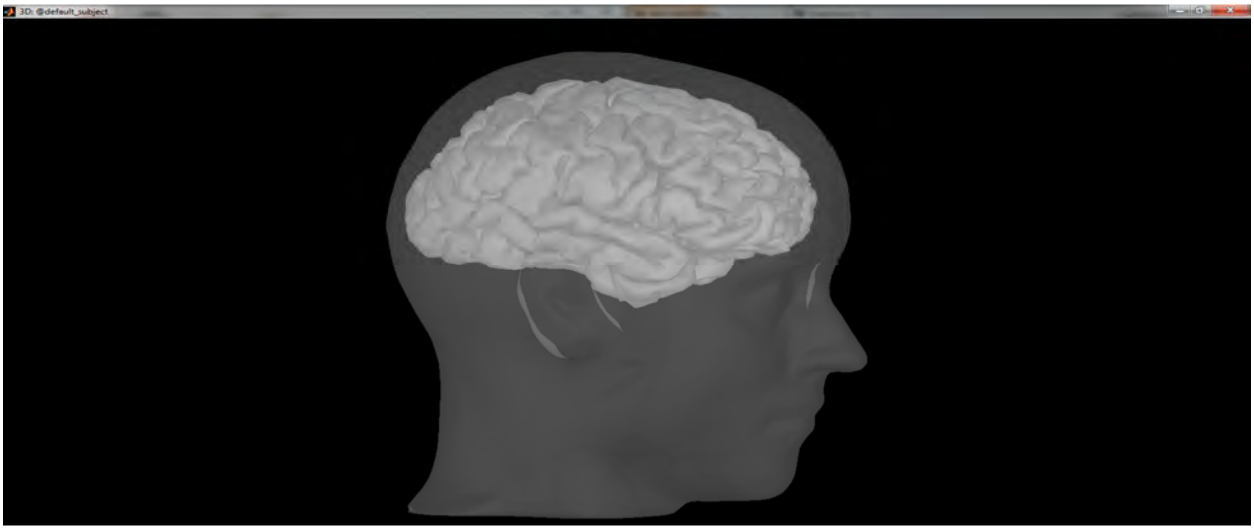


Figure 5-9: Integrating Brain Cortex and Head Model in Time Frequency Analysis

5.14.2 Signal Filtering and Edge Effect Removal

The raw EEG data was filtered using Brainstorm toolbox. Brainstorm toolbox allows for high and low pass signal filtering. The signal filtering procedure removed, signal harmonics, magnetic, electrical contamination and signal edge effects. This was illustrated in figure 5-10_a and figure 5-10_b. Figure 5-10_a shows raw EEG data before filter characteristics are applied and figure 5-10_b shows EEG data after filtration.

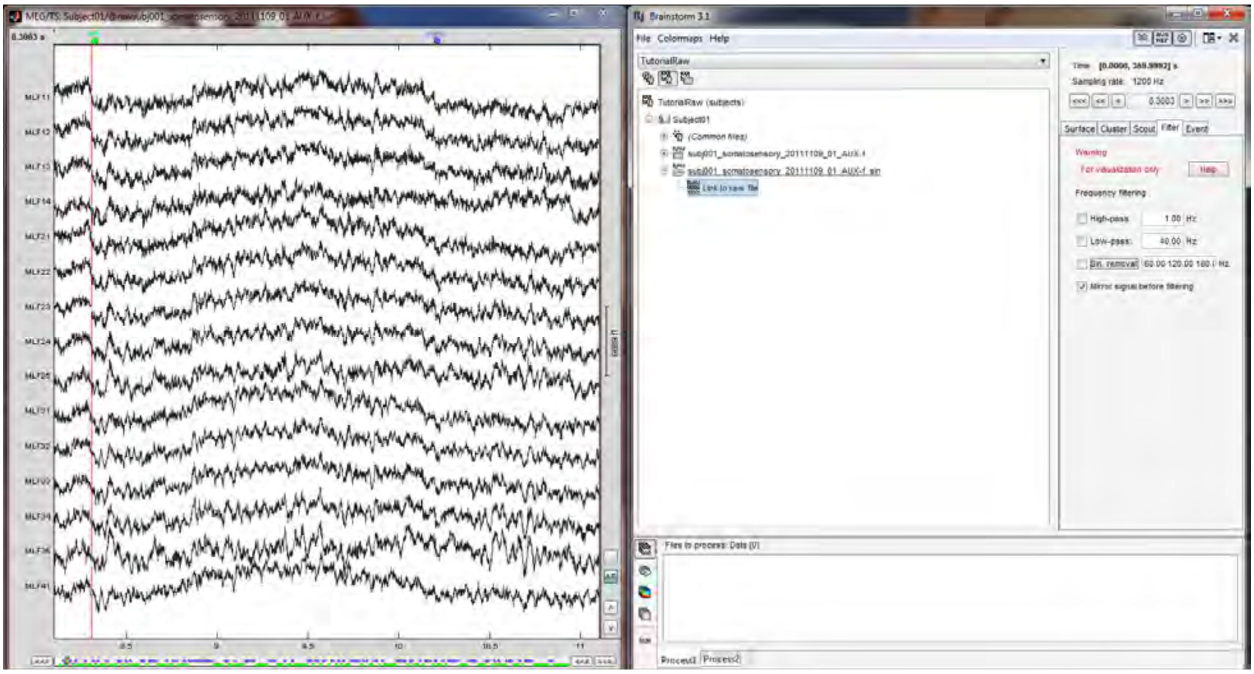


Figure 5-10_a: Raw EEG Data before Filtering

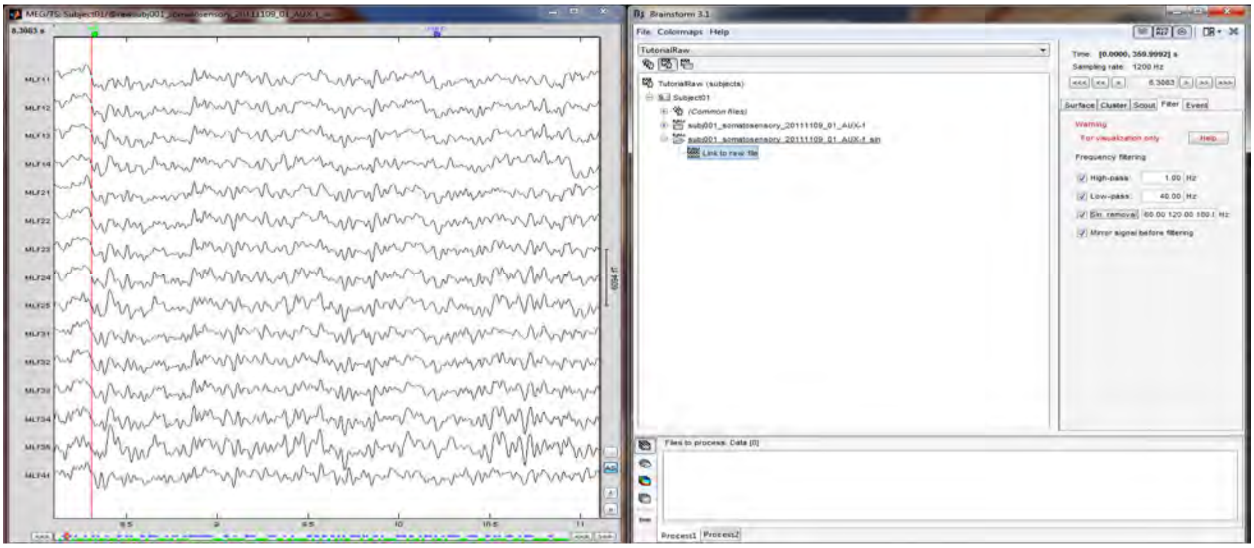


Figure 5-10_b: Raw EEG Data after Filtering

5.14.3 Artefact Detection

Segments of EEG data are usually contaminated by unwanted artefact or artefacts which may not be of interest for a particular analysis. The required artefacts and unwanted artefacts were both identified using special signal analysis techniques. For example, if for a given experiment, the focus was on teeth clenching, the presence of eye blinks in the recorded EEG data was regarded as contamination and vice versa. Artefacts such as heart beats, smirking, smiling, eye blinks, teeth clenching etc. occur may occur at specific frequencies. The occurrence of artefact at specific frequencies allowed for detection and identification using frequency filters. In figure 5-11 peaks from power source harmonics are identified as contamination and are removed before the identification of actual EEG artefacts.

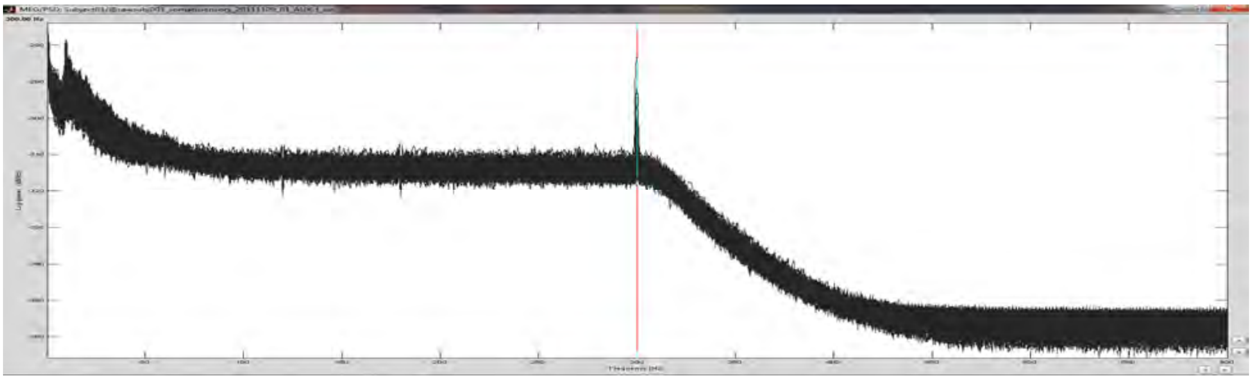


Figure 5-11: Artefact Identified At 300 Hz before Removal

The initial step taken in the identification of artefacts in the recorded EEG data included the use of markers to indicate events or specific neural activity. In figure 5-12, the valley in the red line represents and the corresponding peak in the green line represents neural event at the given time. In this particular exercise, they were regarded as contamination and as such manual markers (red vertical line) were used to identify their frequencies. In the Brainstorm toolbox, eye blinks can also be identified automatically from the EEG data by specifying the event name in the toolbox.

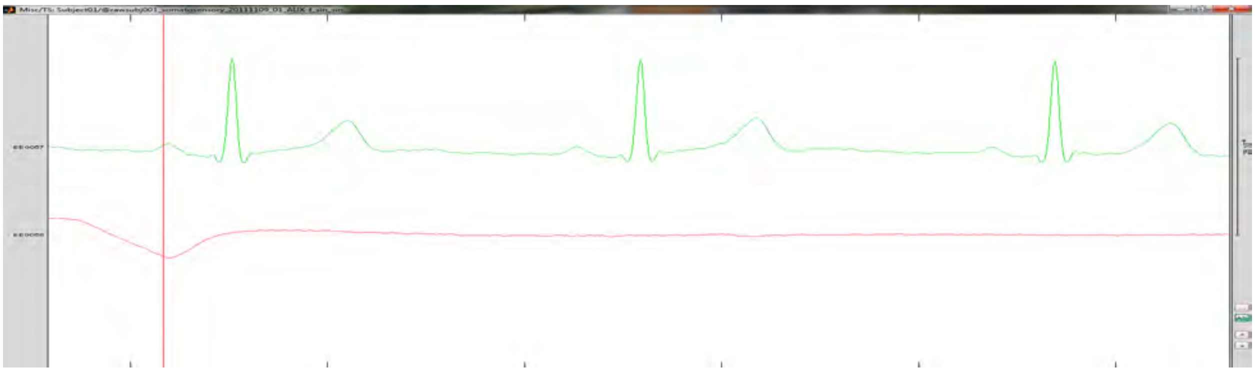


Figure 5-12: Eye Blink Identification

5.14.4 Channel Locations

The EEG channel positions are the electrode placement sites or localities around the scalp. In figure 5-13, the locations and placements for a 32-channel EEG recording device is shown. Given that areas of interest vary from different research objectives, it was not mandatory to record EEG data from 32 electrode locations. The 32 electrode positions provided guidance in accordance to the standard 10-20 EEG electrode placement system

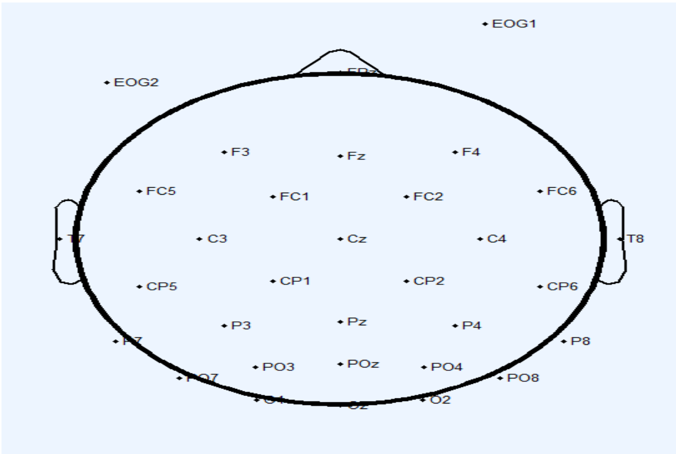


Figure 5-13: 32 Possible Electrode Placement Locations / Channel Locations

5.14.5 Channel Spectra and Maps

In the analysis of EEG data, at the pre-processing stage, bad EEG data segments recorded continuously or bad EEG epochs were rejected. The data rejection process was conducted through direct visualization of the EEG data segments. Bad and inconsistent segments were identified and removed from the Experimental data using EEGLAB. Once the bad segments of the EEG data were removed, the suitability of the remaining data for analysis was checked by reviewing the power spectrum of the data using MATLAB signal processing toolbox. In figure 5-14_a to figure 5-14_d, the properties of the EEG recording channels were investigated by observing the EEG signal power- frequency relationship. This relationship showed that the electrodes were well calibrated and there were no discrepancies in the EEG electrode setup. The activity power spectrum of each of the electrodes shared similar power profiles. The peak frequency in the power activity for each of the electrodes was similar with different corresponding power values.

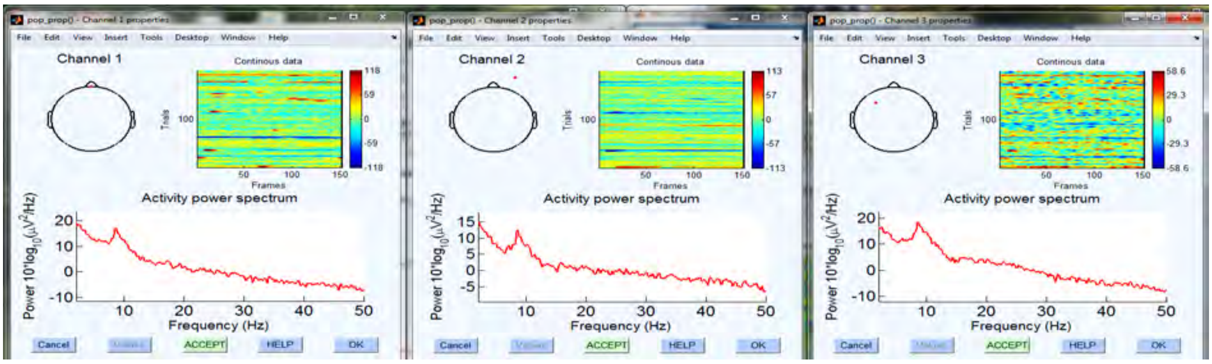


Figure 5-14_a: Channel 1to 3 Property Investigation

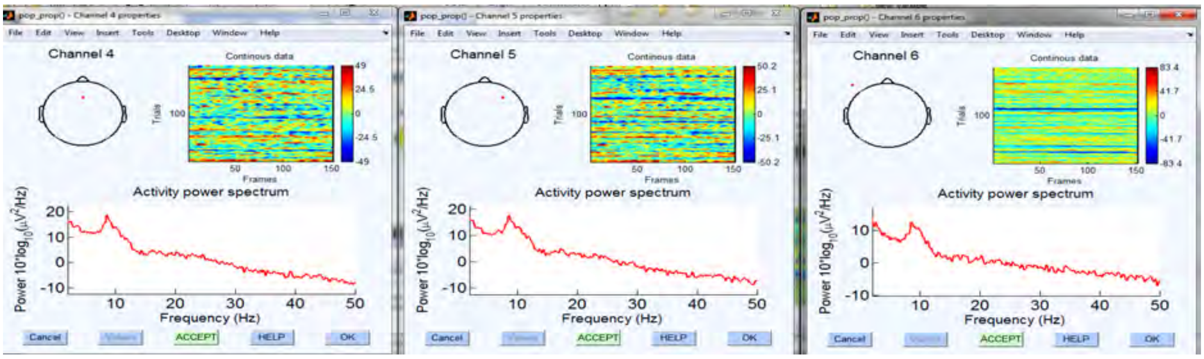


Figure 5-14_b: Channel 4 To 6 Property Investigation

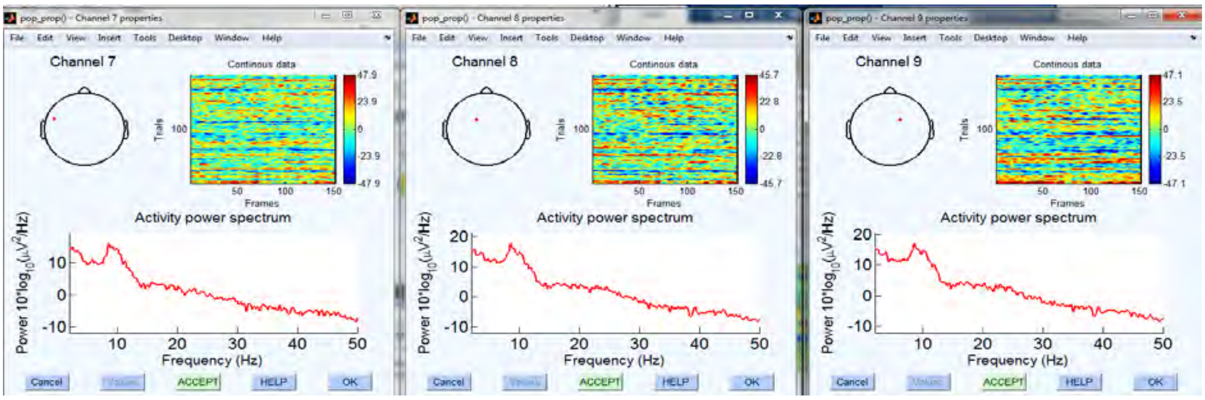


Figure 5-14_c: Channel 7 To 9 Property Investigation

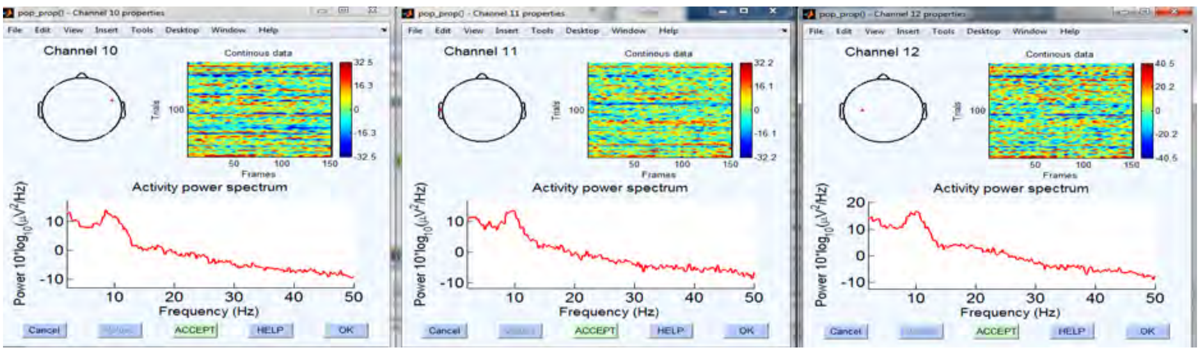


Figure 5-14_d: Channel 10 To 12 Property Investigation

5.14.6 Finite Impulse Filter (FIR) Response

The finite impulse response filter was applied to the EEG data in order to remove line noise. The FIR filter filters the EEG signal in both forward and backward filtering process. The forward and backward filter process removed any signal phase delays introduced by the FIR filter. The effects of phase delays were nullified by the forward and backward filtering process. The EEG data was averaged and epoched after filtering with either a FIR filter or infinite impulse response (IIR) filter. Figure 5-15 indicates results from epoched EEG data and figure 5-16 indicates the results in time series.

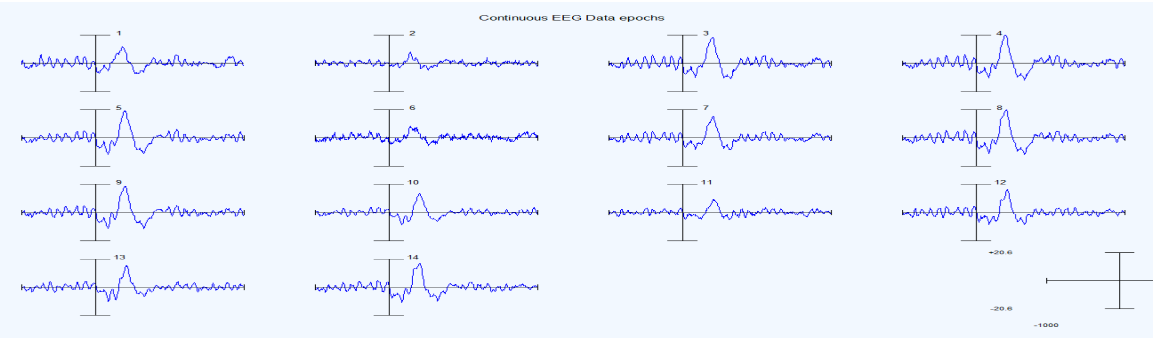


Figure 5-15: Continuous EEG Data Epochs for Each Channel

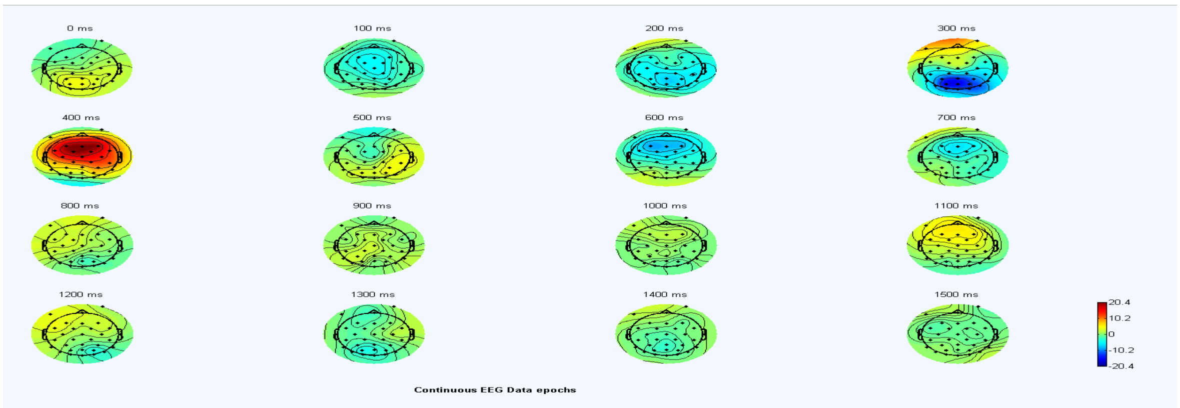


Figure 5-16: Continuous EEG Data Epochs Time Series

5.14.7 PCA Numerical Results

Principal component analysis (PCA) was implemented and used in determining the orthogonality of EEG data within defined EEG vector input space. PCA was also used as the EEG data dimension reduction tool. These pre-processes were instrumental towards the classification and clustering of EEG data. In applying PCA to high dimensional data set such as EEG data, it was worthy to note that the first two or three principal components were necessary in order to visualise and analyse the characteristics of EEG data. In figure 5-17, the first k-components of the PCA algorithm was extracted using probabilistic principal component analysis (PPCA) algorithm. The eight EEG frequency band were used as variables against 150 trials or recordings. The results showed that the first principal components were within 14% to 16% and the second principal components were within 15% to 18% at any given time for random signal such as EEG data

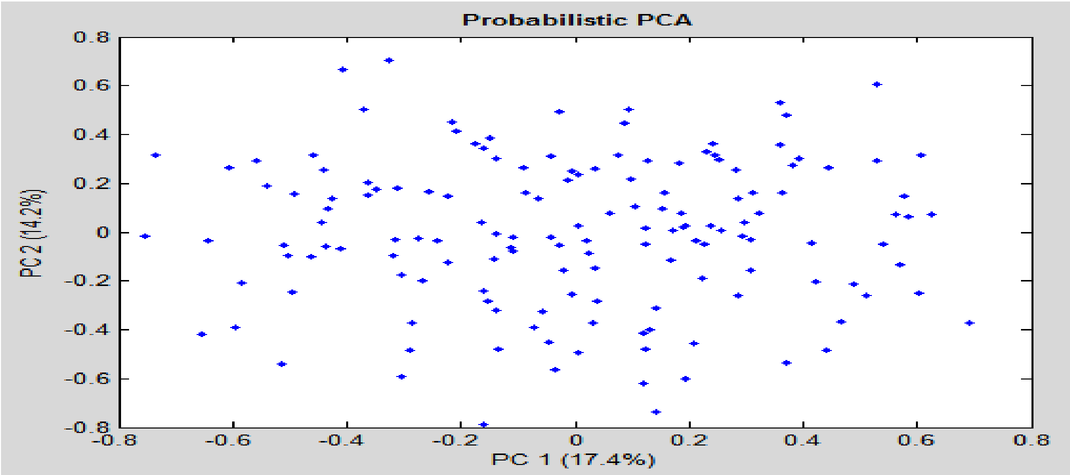


Figure 5-17: First and Second Principal Components

In clustering EEG data frequencies as shown in figure 5-18, the PCA vector space provided for the identification of sub frequency groups within the EEG data. The sub frequency groups may be deemed as noise with respect to the application and analysis at the given instance. These sub frequency groups, when removed allowed for the identification of the EEG artefact of interest. Principal component analysis was also useful in investigating the underlying structure of EEG data. In figure 5-19, the classification of EEG data was achieved using PCA.

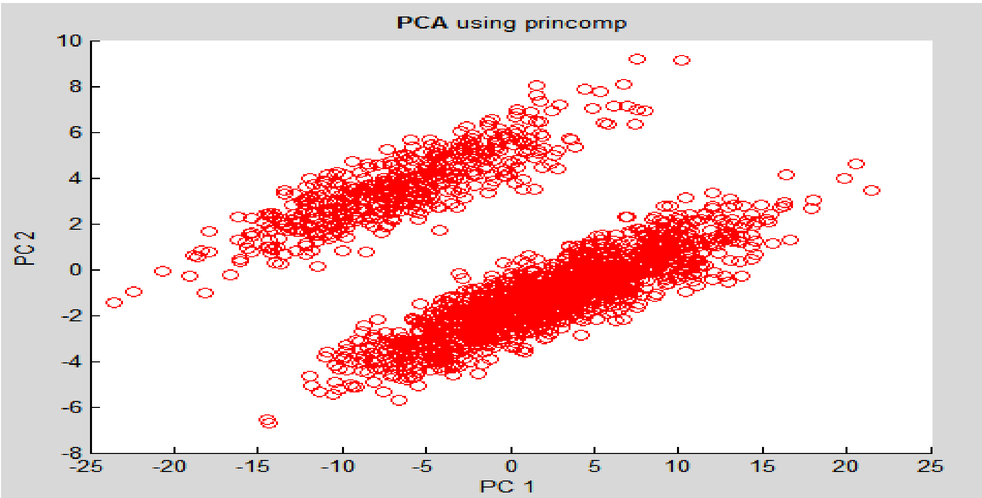


Figure 5-18: EEG Data in PCA Clustering Vector Space

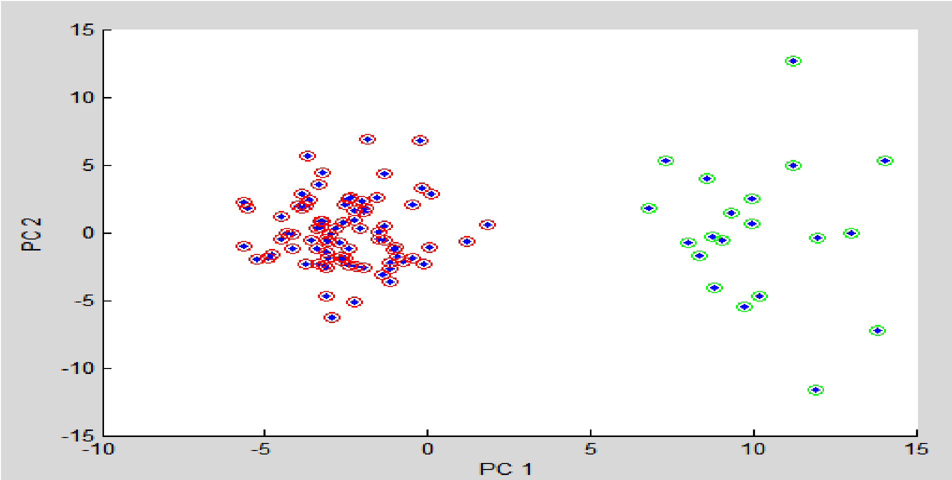


Figure 5-19: EEG Data Clustering using PCA

5.14.8 Logistic Regression Classifier Results

The logistic regression model implemented was such that the characteristic randomness of neural signals generated from the brain was incorporated in the logistic regression algorithm. The logistic regression model was designed such that it was compatible with machine language (i.e. Ones and zeroes). The allocation of ones and zeroes in the algorithm provided manageable thresholds for the binary classification processes. One was defined as EEG frequency of interest and zero was defined as the absence of EEG frequency of interest. During EEG recording, whenever the EEG frequency of interest was recorded, a one was registered and a zero was registered in its absence. It was also noteworthy that the classification of EEG data might not be clinical as there were various sources of noise in the EEG signal. In order to demonstrate the efficacy of the logistic regression classifier, two EEG frequency data points were chosen. In order to increase the accuracy of the algorithm, 50% threshold was allocated to the EEG frequency of interest. The logistic regression algorithm used the weighted sum of each frequency of interest and noise in classifying EEG artefact from EEG data. In evaluating the efficiency the logistic regression algorithm as a classifier, linear predictor and quadratic predictor models were used to check if there were any differences in the in results obtained when logistic regression algorithm was applied to it. Both linear and quadratic models fit the binomial distribution of the test data. In figures 5-20 and figure 5-21, the results from the logistic regression as the classifier is shown while it was validated using linear and quadratic predictors

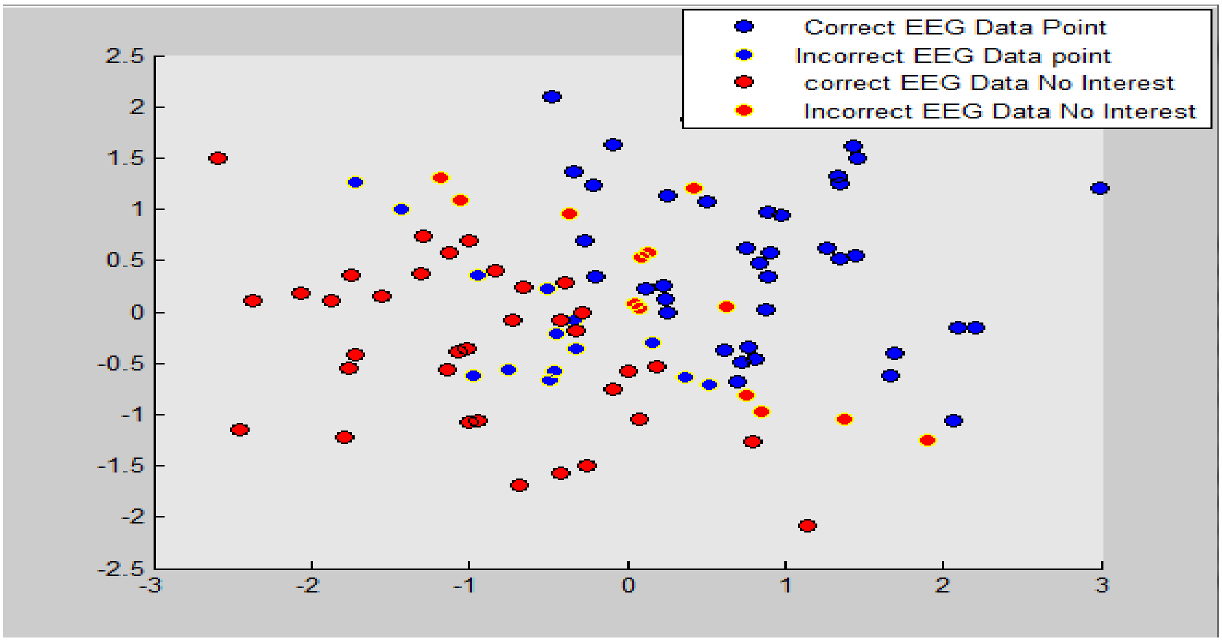


Figure 5-20: Logistic Regression without Linear or Quadratic Predictors

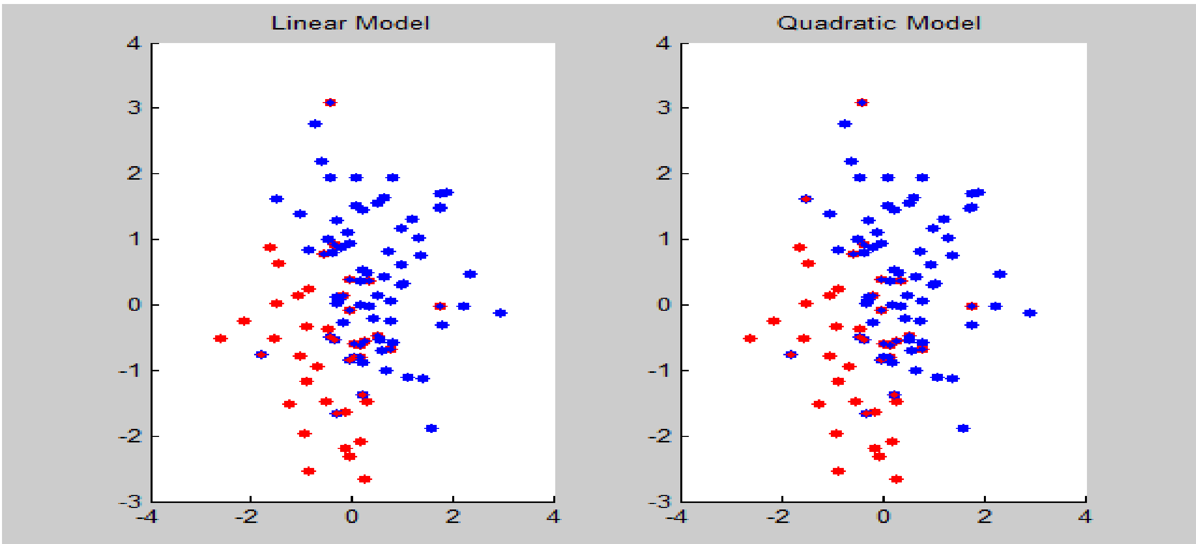


Figure 5-21: Implementation of Linear and Quadratic Predictors in Logistic Regression

In figure 5-22, result from the linear discriminant is shown. The LDA was used to classifier the EEG data into four artefact categories representing EEG frequencies. The analysis sought to ensure that each classification have distinctive data boundary which may not be mutually exclusive with reference to the EEG artefact of interest.

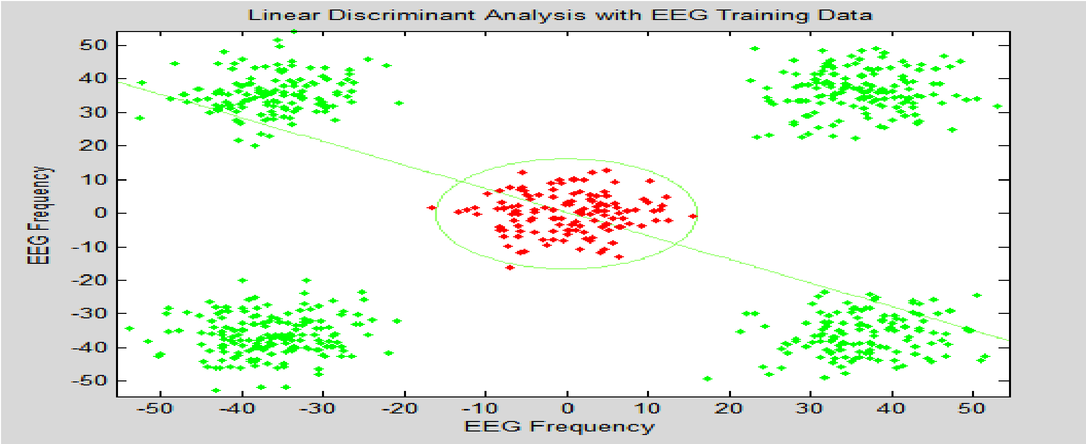


Figure 5-22: Classification Using Linear Discriminant Analysis (LDA)

In using radial basis function as the classifier, the RBF algorithm was initially trained with sample EEG data as shown in figure 5-23. The RBF transfer function distribution profile shown in figure 5-24 provides an indication on the state of deviation from the actual initial EEG data that was fed into the algorithm. The RBF network was then trained as indicated in figure 5-25 and the weighted output shown in figure 5-26 from the network can be used to predict EEG data. The target prediction performance is shown in figure 5-27. The usefulness of the result shown in figure 5-27 was in the development of mechatronic system that are capable of predicting the next motion based on initial EEG data that was supplied to the system. The mechatronic system can perform coordinated semi-autonomous actions and motions.

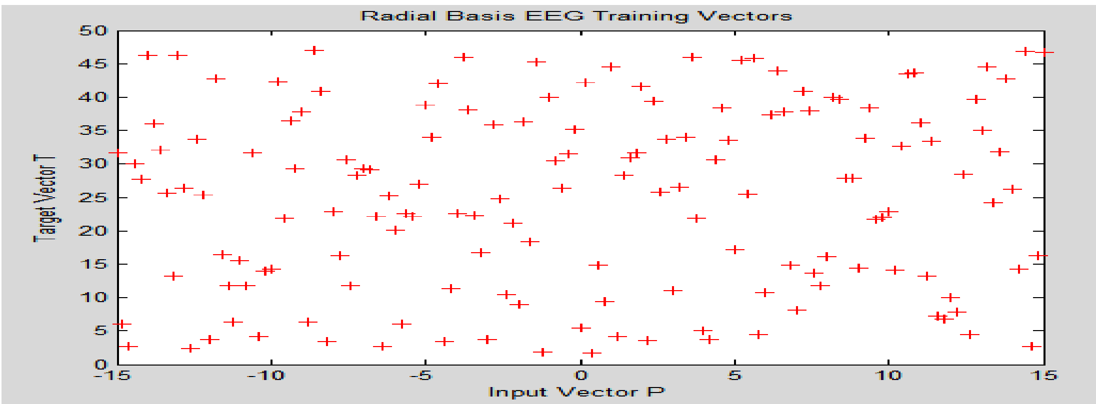


Figure 5-23: RBF Training Vectors

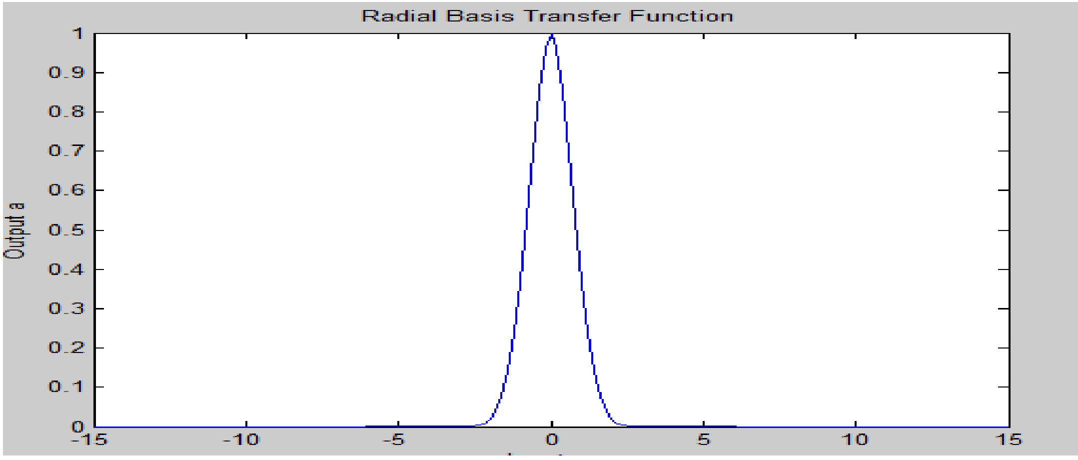


Figure 5-24: RBF Profile Distribution

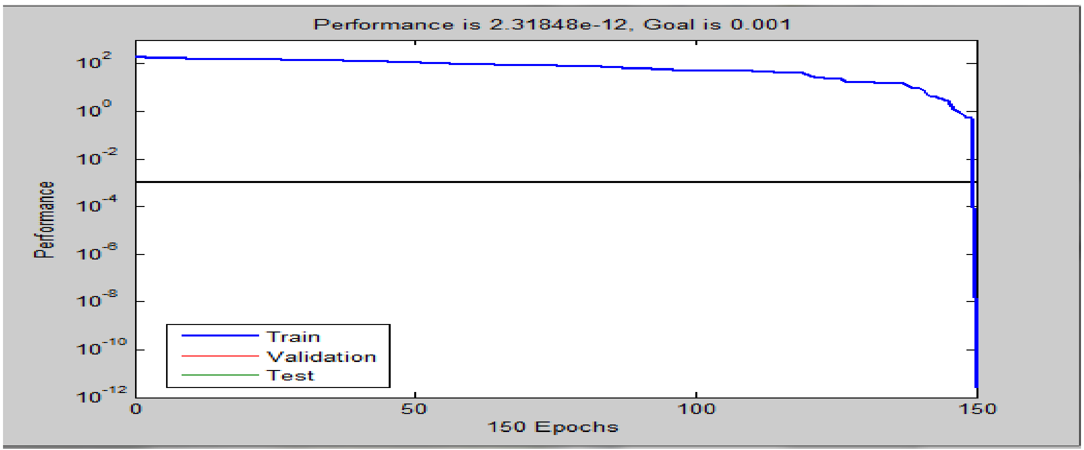


Figure 5-25: RBF Algorithm Training

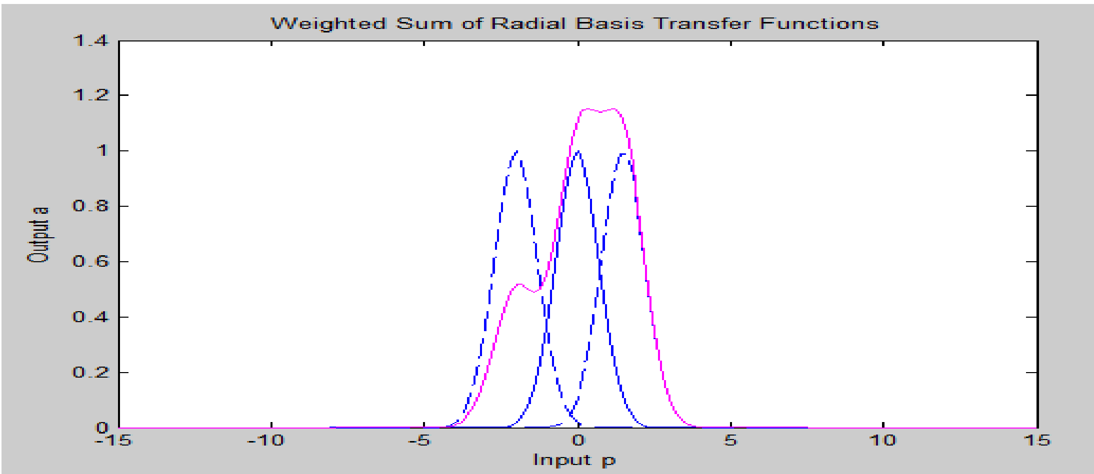


Figure 5-26: RBF Weighted Profile Sum Distribution

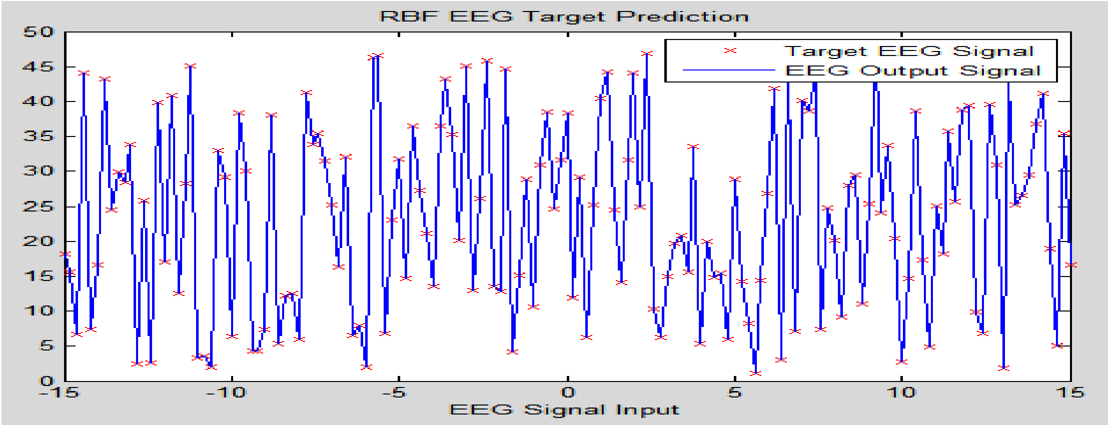


Figure 5-27: RBF EEG Target Prediction

The decomposition of EEG recordings and measured neural activity requires the implementation of wavelet transforms in EEG time series analysis and representations wavelets having the characteristics of a sinusoid scaled by a Gaussian function was used in capturing the local neural activities and signal characteristics in time series. Wavelets have flexible resolution in time and frequency when compared to the standard short-time Fourier transform algorithm. In using wavelet transform in the frequency-time analysis of the EEG recordings, there is a trade-off between EEG spectral and temporal resolution. The time-frequency analysis algorithm provided signal resolution in full width and half maximum the Gaussian function in time and frequency. Wavelet transform was used in de-noising the EEG data. The clean-up process for the EEG data allows for efficient artefact identification. The more the tree decomposition in the wavelet transform algorithm, the more time it takes to de-noise the EEG data. The results shown in figures 5-28 and figure 5-29 indicate the effectiveness of wavelet transform in de-noising the EEG data.

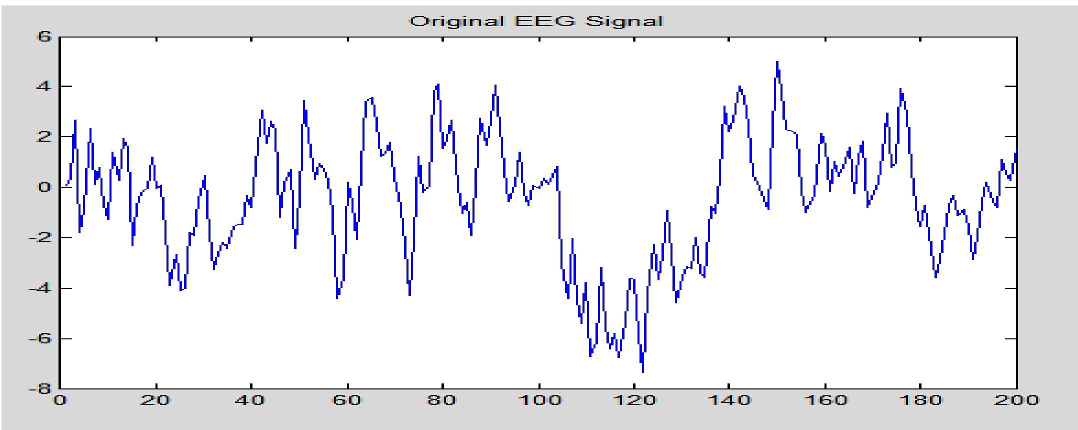


Figure 5-28: EEG Signal before Wavelet Transform

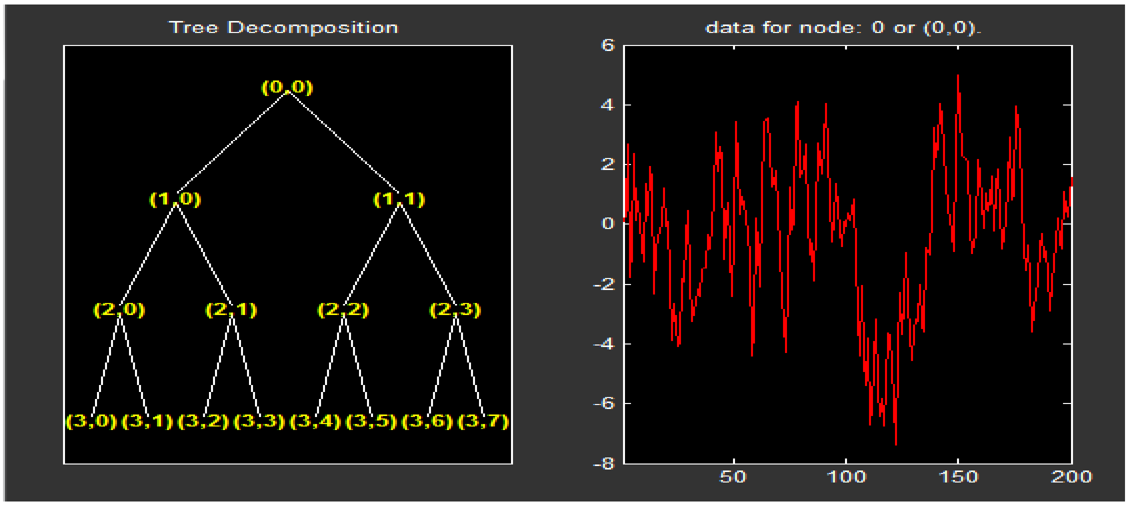


Figure 5-29: EEG Signal after Implementation of Wavelet Transform

FFT algorithm was used to investigate the power spectrum properties of the EEG data. The EEG data was prepared for FFT algorithm and separated to real and imaginary part for analysis as indicated in figure 5-30 and figure 5-31. Figure 5-31 showed the real and imaginary representation of four EEG frequencies which were queued for classification. The power and amplitude spectrum of the EEG frequencies provided useful insights in the effectiveness of the EEG artefact identification process.

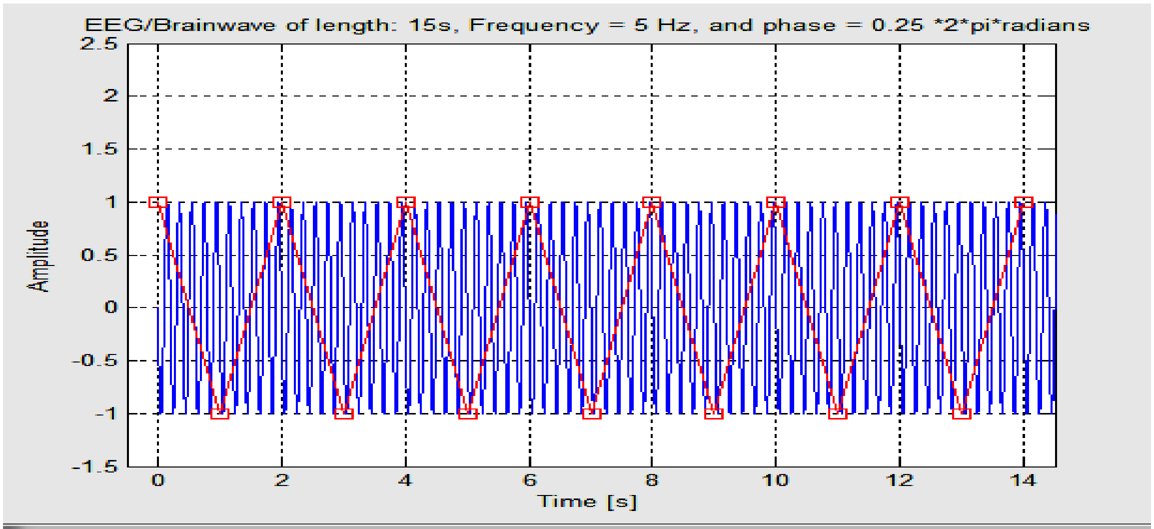


Figure 5-30: EEG Signal Preparation for FFT

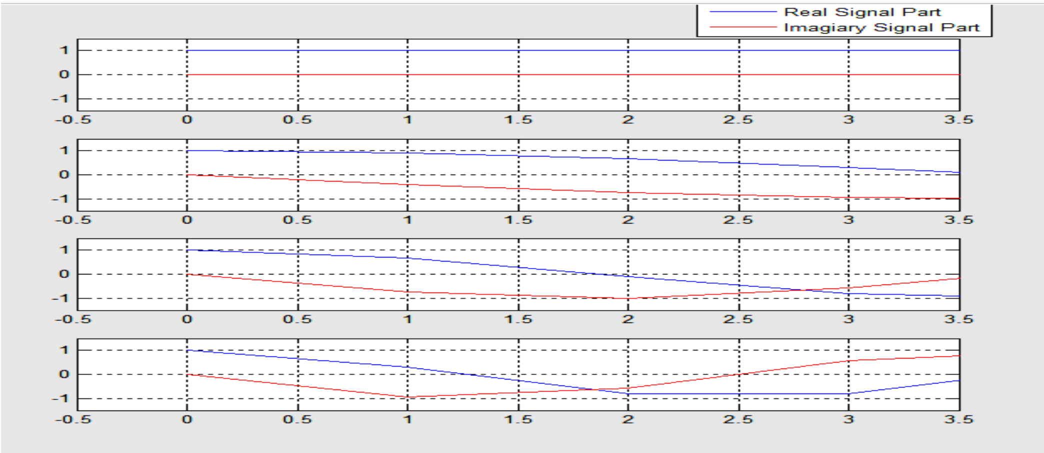


Figure 5-31: EEG signal Real and Imaginary Part

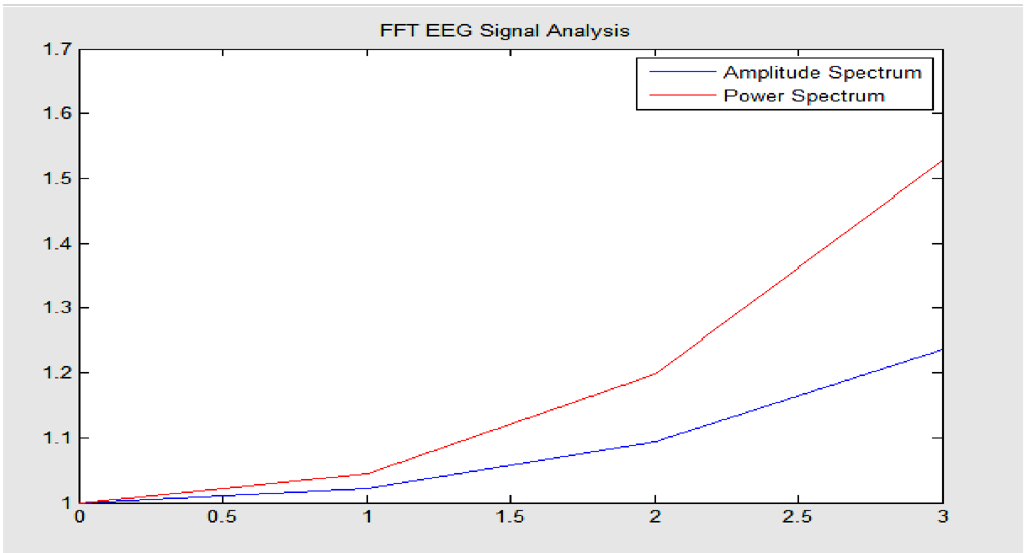


Figure 5-32: EEG Power and Amplitude Spectrum Investigation

In using singular value decomposition as the classifier for the EEG artefact, it was noteworthy that the algorithm provided not only boundary conditions parse but provided data which were instrumental in developing thresholds in classifying EEG artefact. SVD gave an appreciable level of difference on the artefact classification process. SVD was used in conjunction with an RBF kernel to increase its efficiency in the classification of EEG artefact. Results from the SVD algorithm are shown in figure 5-33.

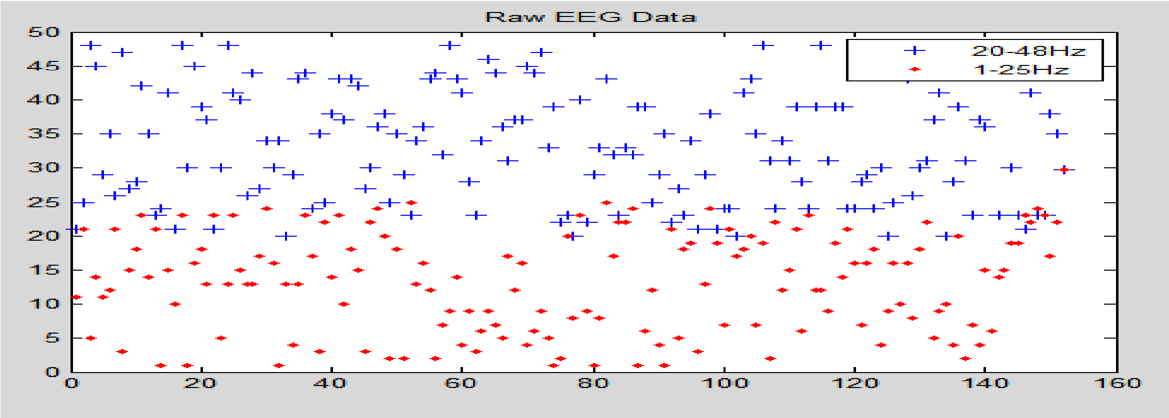


Figure 5-33: Raw EEG Data for SVD Training in Classifying 2 EEG groups

The Simulink design of the MLP network is shown in appendix A-5 and appendix A-6. In figure 5-34. The MSE error of the MLP network required 500ms to converge to zero. The MLP network was designed with four inputs and it has four layers of neurons in the network. In figure 5-35, MSE from incremental MLP network is shown. In comparison between the two training techniques, it was observed that the incremental MLP required more processes as it treated each EEG data separately. The results are the combinations of each EEG data input. The batch MLP processed the EEG data as a single unit and required fewer processes and neurons for the result to converge to zero.

The results from figures 5-34 and figure 5-35 implied that it was computationally efficient to process EEG data in batches rather than individually. Batch processing of EEG data also reduced the time required for features to be extracted. There was better communication within the BCI network as a result of MLP batch process.

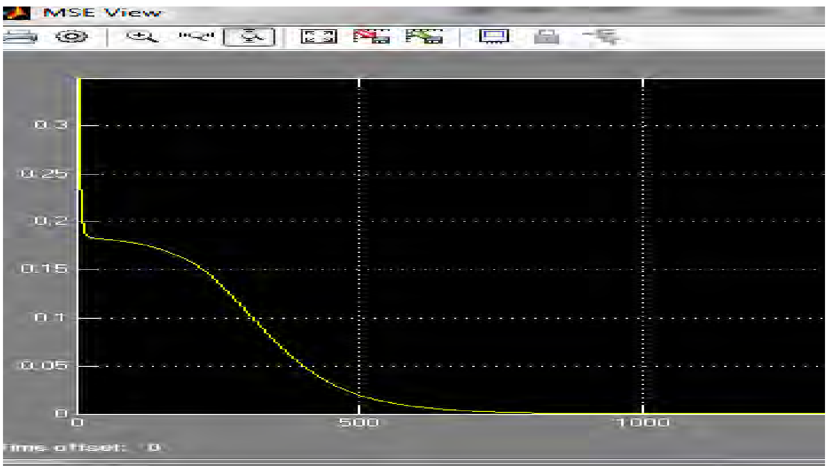


Figure 5-34: MSE from Batch MLP Network

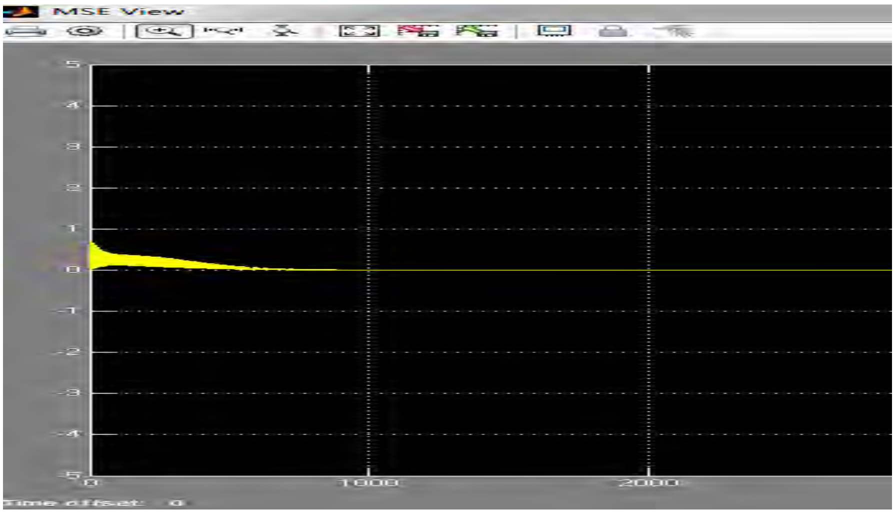


Figure 5-35: MSE from Incremental MLP Network

5.15 Summary

In determining and developing robust bio-monitoring and bio-signal analysis systems for use in semi-autonomous robot systems, the techniques employed in analysing the EEG signals included the use of Radial Basis Function (RBF) neural network, Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Wavelet Packet Transform (WPT), Multilayer Perceptron Neural Network (MLPNN), Learning Vector Quantization neural network, Bayesian and probabilistic paradigms in developing EEG signal identification extraction and classification.

Each of the algorithms discussed in this chapter have their strengths and weaknesses. The efficiency of each of the algorithm was in the implementation, integration and augmentation with the aim of forming hybrid EEG artefact extraction and classification system. Applications of the algorithms were system dependent as embedded system are yet to provide sufficient computing power necessary for full autonomous system integration. It was noteworthy that the results presented in the chapter indicated that no single model was sufficient for efficient EEG artefact extraction and classification for use in mechatronic systems. The need for an efficient hybrid EEG signal analysis system as presented in section 5.13 was deemed necessary. The work presented in chapter 5 was performed in order to develop an efficient and integrated EEG artefact identification, extraction and classification system for the control of a robotic hand.

CHAPTER SIX

Neuro-Symbolic Behaviour Language Modelling

This chapter discusses the application of augmented artificial intelligence in the control and coordination of semi-autonomous robots using neuro-symbolic behaviour language (NSBL) as the robot behaviour prediction mechanism. The mechatronic system behaviour prediction was augmented in distributed intelligent EEG data processing system providing responses to robot behaviour at levels matching the neural activity in the brain.

6.1 Introduction

The ability to communicate with robots and systems were deemed to be influences emanating from the behaviour of an individual (the sender) influencing the behaviour of the system or robot (receiver). Communication using the EEG wireless autonomic system can be defined as the communicative process which reduced the uncertainty in the behaviour the robot or semi-autonomous system [**175**]. Intensely interactive BCI system integrated in cognitive neural-symbolic architecture provided symbolic communication components which were recognizable by the dynamic and adaptive EEG neural processing system. The significant operations embedded in the augmentation of neuro-symbolic language architecture in BCI technology development played critical roles in the mapping and matching of cognitive processes to specific robot motion and actions. The strengths and weaknesses of the intelligent neuro-symbolic system provided estimable basis for EEG artefact pattern recognition given the high dimensional nature of EEG data. Syntax processing and abstract reasoning towards EEG artefact recognition and differentiation were the characteristics which were useful in the mapping of cognitive processes to robotic motions. The objective for the system integration was to maximize the advantages of both the neural and symbolic language architectures. The peculiarity in autonomic neural systems and symbolic artificial intelligence systems was in the semantic network rules and integration strategy. Knowledge and information derived from EEG data can be represented locally or globally in the overall augmented neuro-symbolic architecture. In using EEG electrodes as sensors in the BCI system, the connectivity between intelligently coded knowledge and information with logic allowed the proposed system to be neuro-symbolic rather than being only symbolic or neural system. This gave the integrated system the edge and advantage on being stable as data security issues and information transmission and mapping were effectively managed.

6.1.1 Chapter Motivation

The work presented in chapter 6 was performed in order to use neuro-symbolic behaviour language system in the selection and management of the robotic hand motion using EEG artefact. The communication and the distributed intelligence system was developed in order to manage high-level computing and transmission of EEG data.

6.2 Symbolic and Neural Communication

Neural systems have complex arrangements for their neurons. The dynamically structured neural net allowed the neuro-symbolic system to be a step from brain modelling to purpose driven intelligent system for controlling semi-autonomous system. The paradigms shared by the neuro-symbolic system were appreciated more in embedded systems as memory allocation and usage were critical in the processing and transmission of EEG data. The conceptualisation of the neuro-symbolic system was based on memory allocation especially in the microcontroller and graphic processing units (GPU). In the BCI system requiring specific artefacts for system activation, there were sets of cognitive events or cognitive activities of interest which were given memory allocation as the percentage of full system internal processes. The degree of system membership in terms of memory usage and allocation provided the language level indication. The language level indications were grouped into global and local communication strategies. The interaction between human beings and robots using these two levels of communication provided the basis for the neuro-symbolic language modelling for BCI technology development [**176**].

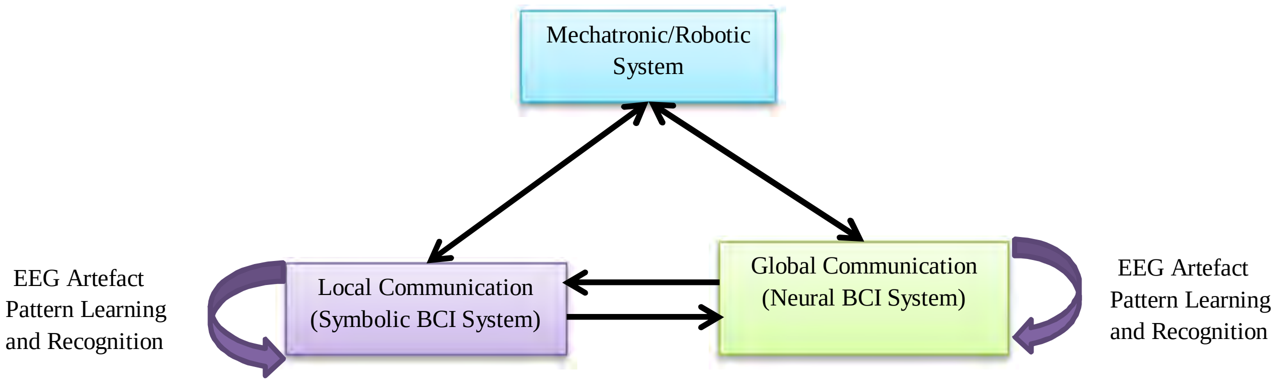


Figure 6-1: The Generic Neuro-Symbolic BCI Architecture

In order for BCI system to have the ability to integrate knowledge based intelligence and learning with mapped responses from dynamic sets of cognitive activities; the behaviour models of robot actions and motions were determined using neuro-symbolic behaviour language. This enabled the BCI system to specify and issue out control protocols involving non-monotonic control actions. Reactive and deliberative robot motions were modelled uniformly while considering the neural and logical architectures of the BCI system. The neuro-symbolic behaviour language showcased the BCI system decision making structure as EEG data were being analysed. Robotic motions bounded by time responses were carefully selected through sequential motion control protocols. The neuro-symbolic behaviour language modelling strategy utilised the adaptive properties of the EEG neural network and the sub BCI system capacities. Considering the robotic motion of moving forward, asynchronous EEG signal and artefact were used as robot motion control inputs. These inputs determined responses experienced by robot end effectors. In managing such control, coordination sequences and strategies, the neuro-symbolic behaviour language used the UNLESS and IMPLY strategy. These were key syntaxes to manage robot motion control inputs [**177**]. The proposition introduced by the neuro-symbolic behaviour language sets the rules for monotonic and non-monotonic in the BCI intelligence system. The NSBL reinforced the strategy required in EEG artefact identification and classification.

In demonstrating the NSBL proposition in managing decision making in the BCI intelligence architecture, the EEG artefacts were associated with the cognitive component x_i having specific neural firing x^i. The certainty value of each proposition can either be True, False or Undefined. The firing state of each neuron in the EEG neural network determined the weighted value of the threshold set for the identification of each EEG artefact. In order to encode the EEG artefacts adequately, the negation of cognitive component and specific neural firing were represented as $\sim x^i$ and $\sim x_i$. The undefined states of the EEG artefacts were represented by the inactivity of the cognitive components. The purpose for incorporating this type of representation in BCI system intelligence development was to encompass the possibility of robot motion given that there can be inactivity, false artefact or false control signal. The execution of robot motion differed significantly in the absence of control signal from the presence of control signal. The BCI system intelligence reacted differently to either false, true or absence of truth value for each artefact of interest.

Given that $G = \{g_i\}$ $(0 < i < n)$ and $H = \{h_i\}$ $(0 < j < m)$ represents the sets of propositional EEG artefacts for $n, m \in N$. Let $G_\wedge$represent the conjunction of EEG artefact components of G and let $H_\vee$ represent the disjunction of EEG artefact components of H. Let q represent the rule. The neuro-symbolic language composed as IMPLY $(G_\wedge, \ q)$ was deduced as "IF the conjunction of EEG artefact $G_\wedge$ is true THEN q is true" and UNLESS $(G_\wedge, H_\vee, \ q)$ was deduced as "IF the conjunction EEG artefacts $G_\wedge$ are true and the disjunction of EEG artefacts are false or undefined THEN q is true". Three-valued truth tables can be generated based on the EEG artefacts, conjunction and disjunction events which are dependent on the type of motion of interest and EEG frequencies of interest. In creating upper and lower boundaries for the neuro-symbolic behaviour language, two additional syntax and operators were introduced. They are ATLEAST and ATMOST. The ATMOST and ATLEAST syntax were used as follows: ATLEAST $(G_\vee, \ l, q)$ was deduced as "IF $j = l$ artefacts of disjunction $G_\vee$ are true THEN q is true" and ATMOST $(G_\vee, \ l \ , q)$ was deduced as "IF $j = l$ artefacts of disjunction are true THEN q is true". The constructs IMPLY and UNLESS adequately constructed formed the set of neuro-symbolic behaviour language rules

6.3 Neuro-Symbolic Tagging

Neuro-symbolic tagging of EEG artefacts was proposed as the intelligence in the parsing of semi-autonomous system control language. The concept proposed in this section was to identify the semi-autonomous system control language context with respect to the EEG frequency. Given that the general objective of the neuro-symbolic behaviour language construct was to integrate the symbolic systems, syntaxes with artificial intelligences having neural networks as the core structure. The mining and extraction of EEG artefacts towards the development of robot control commands provided the semantic syntaxes which were purely associated with cognitive tasks and information. This type of EEG data analysis allowed for the detection of several possible cognitive entities which were useful for control mechatronic devices and systems. Extraction of artefacts which are knowledge domain dependent can be adapted to better suit the coordination and control requirements of mechatronic systems.

6.3.1 The Neural-Symbolic Tagging System

In this section, the neuro-symbolic system is proposed and presented. The neural symbolic tagging system utilized four basic proposition models. These models are:

- In the pool of contextual EEG frequency window or band there are n EEG artefacts
- Each artefact was represented by its probability vector $A_i \in \mathbb{R}^j$ in the pool of contextual EEG frequency
- The resulting probability of the neuro-symbolic tagging system was computed and represented as $A \in \mathbb{R}^j$
- The EEG artefact tagged with the maximum probability was considered to be adequate result for the system

In order to tag EEG artefacts, n-contextual EEG frequencies were considered and represented as the probability distribution of the neuro-symbolic tagging system. The EEG artefact tag relevance vector was computed for the EEG artefact k and the maximum component was selected as the result of the tagging process [**178**]. The neuro-symbolic tagging system learns and computes the function $f: \mathbb{R}^{n \cdot j} \rightarrow \mathbb{R}^j$ where j represents the number of possible EEG artefact tags within the given EEG frequency band and n representing the EEG frequency window or band.

The intended outcomes of the neuro-symbolic tagging system in tagging EEG artefact set was modelled using the probability vector $\left(P_a(T_1), \dots, P_a(T_j)\right)$ assigned to the EEG artefact of interest. The modelled is presented as:

$$P_a(T_i) = \frac{freq(a,T_i)}{freq(a)} \tag{6-1}$$

Where $freq(a, T_i)$ represents the number of times artefact a was tagged as T_i varies within the bounds $(1 \leq i \leq j)$. $freq(a)$ represents the total number of manifestations of artefact a in the EEG frequency band. The computation of global probability vector was used to reflect the relative frequencies of unknown EEG artefact tags which can occur once in the EEG frequency domain.

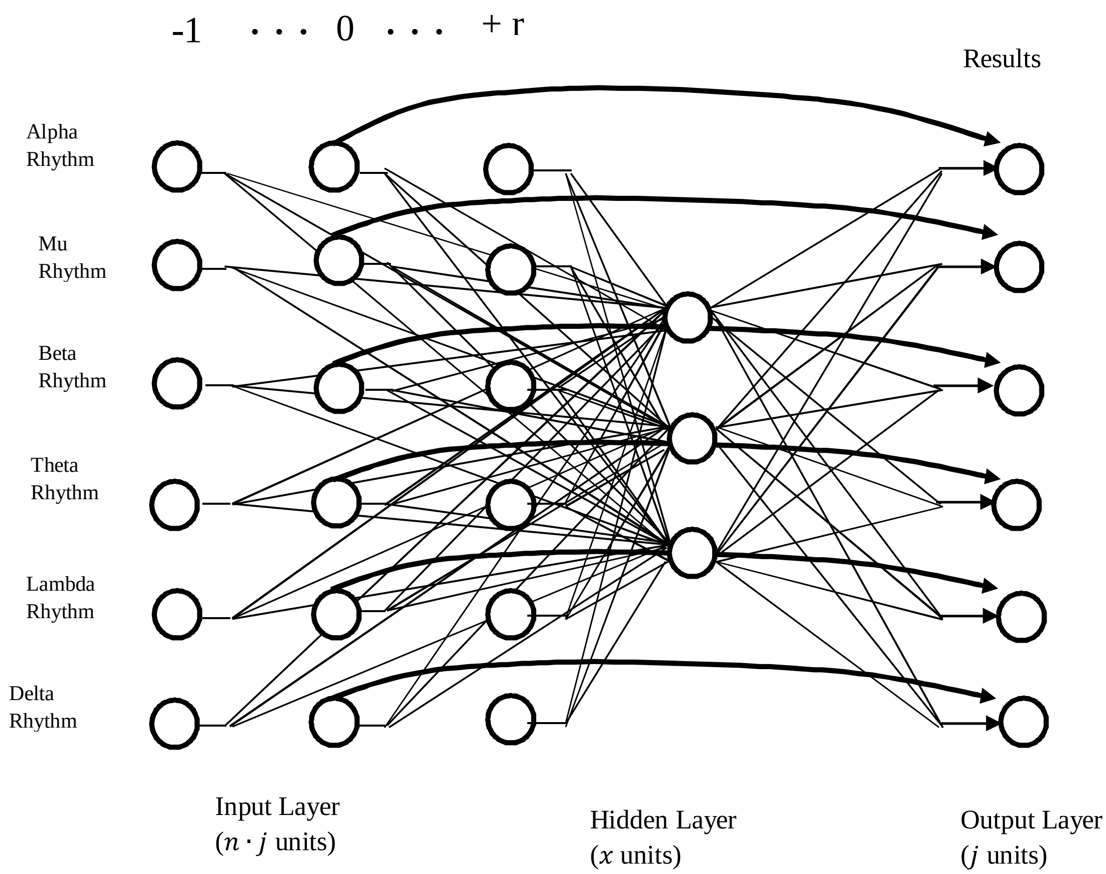


Figure 6-2: The General Architecture of the Neuro-Symbolic Tagging System

6.4 NSBL Integration and Robot Action Selection

The substantial advancements made in the integration of neural networks systems for various robotic and mechatronic system applications have approached noticeable level. The robotic and artificial intelligence community are striving to obtain optimized mechatronic and robotic systems at this level. Variety of logical paradigms used in neural network augmentation provided useful techniques towards the integration of artificial intelligence, neural network and brain computer interface systems. Neural cognition was very important in the development of BCI systems. The symbolic representation of cognitive knowledge in neural networks proved to be useful considering that modern systems are designed to be small, fast and efficient in their functions. In process raw EEG data, the BCI system embedded with artificial intelligence acquired knowledge about the extraction and classification of EEG artefacts. The BCI system learned the processes required to generalise EEG artefact extraction and classification against similar new raw EEG data. The ability of the BCI system to recognise EEG artefacts and classify them facilitated the process of using the classified artefacts for robot motion or action. The classified EEG artefacts were then associated and assigned robot motion and action. In completing this process, the neural-symbolic language was required to efficiently associate classified EEG artefact to robot motions and actions. The neural-symbolic behaviour language integration process utilized the learning cycle shown in figure 6-3 to learn, represent and associate EEG artefacts to robot motion.

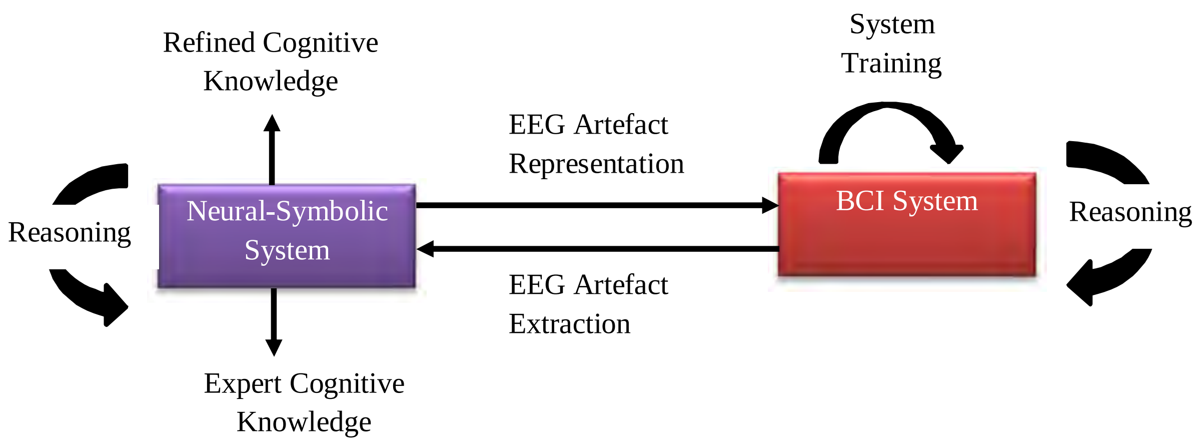


Figure 6-3: Neural-Symbolic Learning Process

In the wake of artificial intelligence systems and automata theory, the neural-symbolic system integration was proposed to be integrated into BCI technology systems. The integration process between BCI technology systems and neural symbolic systems took advantage of simple logical conjunctions, disjunctions and negations in programming the BCI systems using binary thresholds and weights that were realistic.

Result 1: Considering the simplified autonomic neural system represented as the states machine shown in figure 6-4 and 6-5 with outputs attached to the neural network states. The neural network consisted of four layers which were the input layer, the logical gate layer, the state layer and the output layer. The logical gate and the machine state layers were considered to be the hidden layer in the general architecture of the neuro-symbolic system. Considering four EEG frequency bands as inputs, there were associations for each of the EEG frequency bands with the network output signals. The associations were classified using the binary representation (0, 1). Considering the individual input states (G_0, G_1) for each frequency band for the EEG autonomic system, the unit state-layer was linked to the input layer. In ensuring that usable EEG frequencies were not discarded in the neural network computations, the state G_1 can be attained using two possible paths. The state was obtained either by being in state G_1 and receiving the upper bounds of the EEG frequency domain or by being in state G_0

and receiving the lower bounds of the EEG frequency domain. The process was implemented using the disjunctive neuron in the state-layer and conjunctive neurons in the gate-layer were linked to the specifications of the neural architecture. The neural network can be operated using n binary thresholds. For each of the EEG frequency bands, the number of possible states was given by 2^n. The change in the states for each frequency band was dependent on the frequency domain used at the neural network inputs. The states of the neuro-symbolic network can be programmed using direct translation of the neural network in finite automated system.

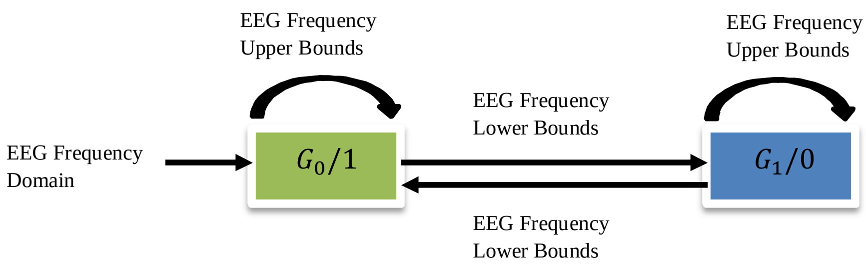


Figure 6-4: EEG Neuro-Symbolic State Machine

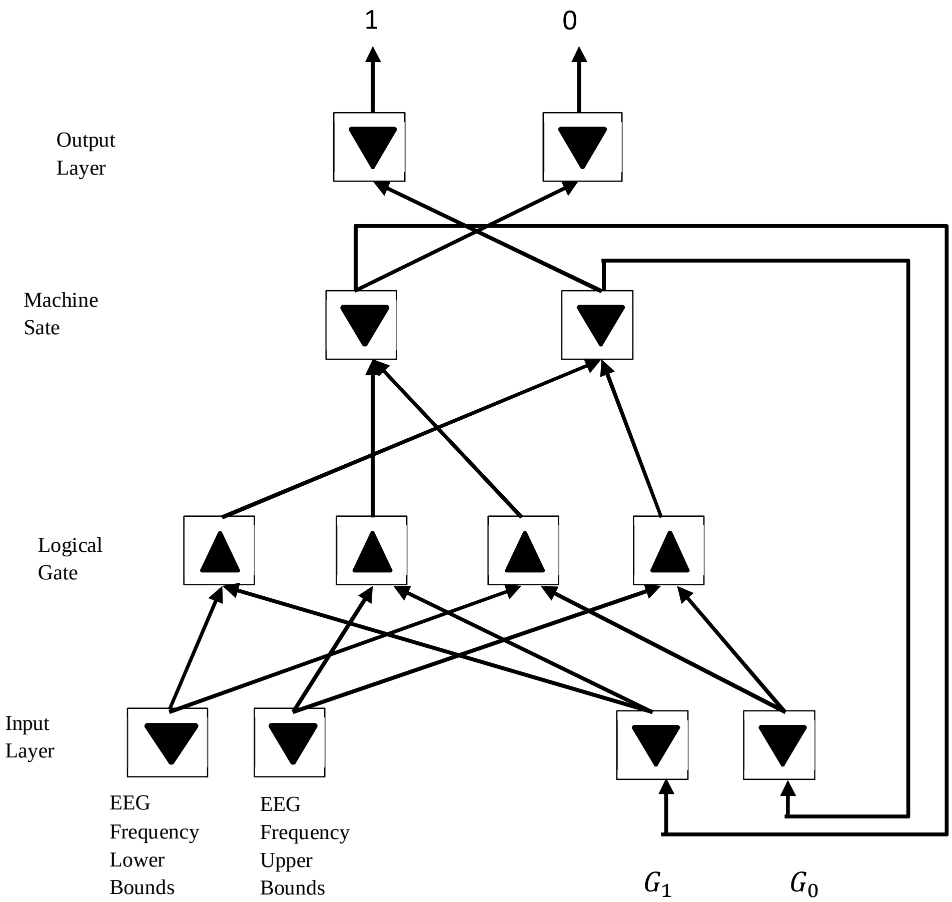


Figure 6-5: Simplified Neuro-Symbolic Machine Processing EEG Frequencies

Result 2: The real vector having the fixed EEG data length representing layers of EEG artefact extraction subsystem was turned into an expert system using the encoder-decoder model. The network was managed using the Recursive Auto-Association Memories (RAAM) technique. The recursive auto-association memories method ensures that the system recognised the EEG artefact of choice through system training. In order for the RAAM system to be effective, the neural network input activations were reproduced at the output layer through the compressed representations of EEG data at the neural network hidden layer. The convergences of the network trainings yields $E = E', F = F', G = G'$ and $H = H'$. The internal network values are stored in K_3. The embedded information in K_3 was useful in the RAAM system.

Table 6-1: Training Model for the RAAM System

Input Layer		Hidden Layer		Output Layer
(E F)	→	$K_1(t)$	→	$(E'(t)\ F'(t))$
(G H)	→	$K_2(t)$	→	$(G'(t)\ H'(t))$
$(K_1(t)\ K_2(t))$	→	$K_3(t)$	→	$(K_1'(t)\ K_2'(t))$

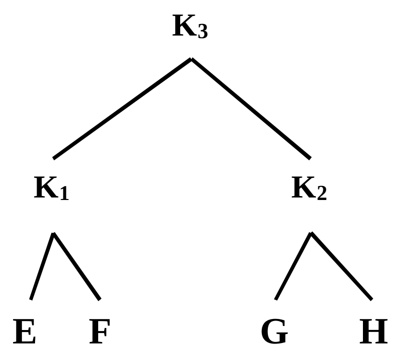


Figure 6-6: RAAM Binary System Architecture

6.5 Distributed Intelligence Processing System

Distributed intelligence processing system encompassed the integration of high-level computing system, information management system and embedded technology system. With respect to this study, distributed intelligent processing system was the collection and collation of independent sub-neural systems working together as a coherent BCI system. In order to ensure that the sampling rates of EEG data were accurate and reliable, the high-level computing system performed the much required high performance computing tasks. The integration of the various sub-systems to form workable BCI technology was aimed at developing the system that was scalable for different mechatronic and robotics application. The system was modelled to be an open system capable of being distributed across autonomic neural network. Making the system user friendly and accessibility of EEG data were the major focus towards the integration of DIPS into BCI technology development. The degrees of information transparency across the autonomic neural network and openness of information across the EEG neural network were factors that determined the interoperability and portability of the distributed intelligence processing system.

System performance was of crucial importance in the development of the DIPS for EEG neural network. Various processes associated with the identification, extraction, classification formed the building block for the DIPS. Threads in distributed systems were virtual processor activities which ran different processes. The processes were regarded as the execution of the functional program on the virtual processors [**179**]. The creation of threads in microcontrollers and microprocessors allowed information derived from EEG data to be executed using minimal system resources. Speed and efficiency were gained through multithreading of EEG data.

6.5.1 Communication in Distributed Intelligence Processing System

Communication in the distributed intelligence processing system formed the core inter-process relationships existing between the different hardware integrated to form BCI technology. Adequate evaluation of the communication processes between each hardware provided ways of integrating low-level information transfer between systems in the EEG autonomic neural network. The difficulty in executing robotic motions was in the inability of the various communication architectures to pass the intended information through to end user seamlessly without the use of shared memory. Low-level communication introduced low-level information distribution transparency and was not suitable for high level message orientated information transfer to mechatronic devices [**179**]. In using low-level information transfer in the distributed intelligence system, it created the absence of shared memory between communication processes. Each communication process created its own message address before the information was transmitted across the wireless autonomic neural network. Communication processes were required to be in agreement before information could be transmitted. In complex robotic motion execution requiring many commands, it followed that many different agreements and addresses were needed before data can be adequately transmitted.

6.5.2 Message-Oriented Information Transmission

The inadequacies experienced in the use of distributed communication processes such as Remote Procedure Calls (RPC) concealed information transmission while enhancing information transparency in distributed communication systems. Other communication methods were required to bypass the blocking of information transmission process while waiting for it to be processed. In the development of BCI technology, various middleware solutions provided the platform necessary for integrating simple

BCI messaging and information transmission system. The middleware solutions integrated in information transport layer architectures provided the required message-oriented model necessary for BCI technology development. Important to the integration of the transport layer was the transport-level communication sockets. By definition, “communication socket was the communication end point to which an application or middleware could write data that were to be sent over the underlying network from which the incoming data could be read. Communication socket formed the abstraction required over the actual communication end point that was used by the local operating system for the specific transport protocol” [**179**]. The use of socket connection-oriented communication in EEG data transmission required the use of the following processes: socket, bind, listen, accept, connect, send, receive and close. The socket created the new EEG data communication end point, the bind process attached the local communication address to the socket, listen announced the willingness of the socket to accept connections, the accept process blocked the caller program until the connection request arrived, the connect process actively attempted to establish connection, the send process sent EEG data over the connection, the receive process received EEG data over the connection and close process released the connection. The socket communication model is shown in figure 6-7.

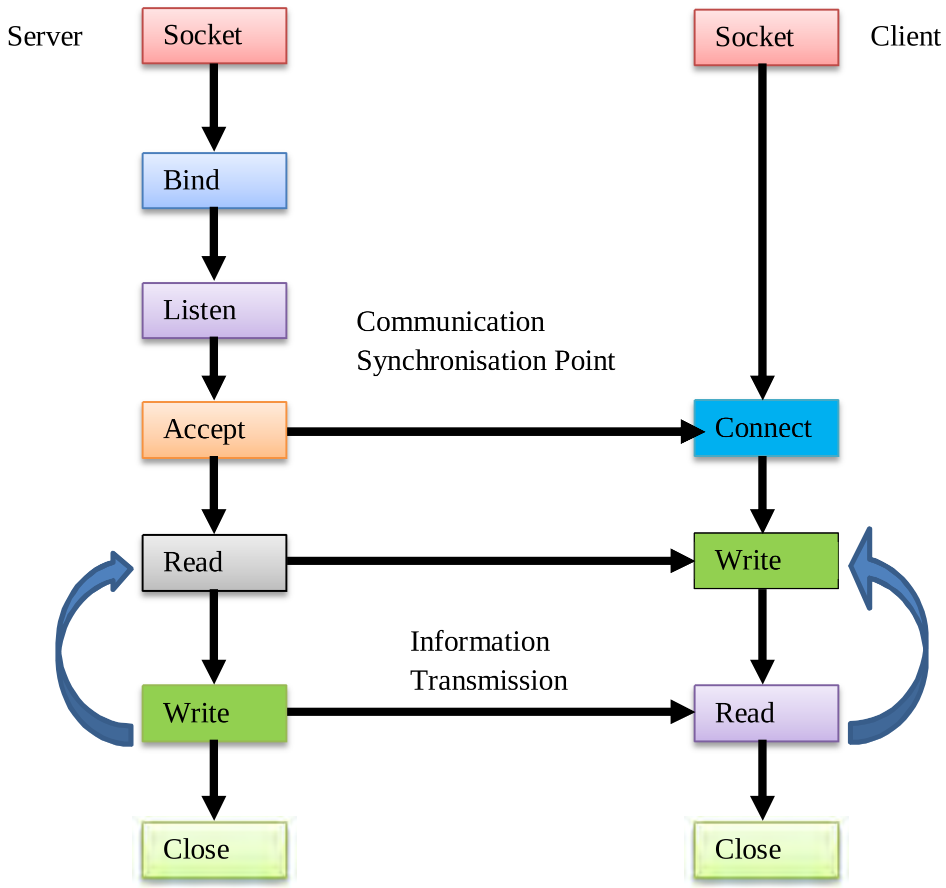


Figure 6-7: Information Transfer Architecture Using Sockets (Connection Oriented)

In order for robotic motions to be synchronous and autonomous and executed within known group of EEG data, Information-Passing Interface (IPI) for parallel EEG information transmission was required for transient EEG data. Under such process, each EEG data was assigned an identifier associated with EEG signal source and destination. There can be few overlapping processes at the execution of the robotic motion algorithms and processes. High speed inter-connection was deemed necessary for EEG data transmission and as such socket connection provided inadequate level of communication abstraction for EEG information transmission. It supported simple send and receive data transmission process using general purpose communication stacks which were very slow for high speed proprietary interconnection wireless networks. The implication of this communication abstraction was that the EEG communication setup required further high level interface with advanced options which included EEG data synchronisation and buffering. With advent of various EEG data acquisition systems, communication between each system and the robots was mutually incompatible. This introduced issue of portability and adaptability of the EEG hardware to different mechatronic and robotic system. Information-passing interface was used in creating adaptable EEG data passing interface. At the prime objective of the information-passing interface was the transient data transmission support. With transient asynchronous communication, EEG data was initially transferred to a local buffer. The information-passing interface transmitted the data immediately after the receiving end has made a receive protocol.

6.6 EEG Data Identification and Naming in DIPS

In the EEG distributed intelligence system, EEG data identification and naming were crucial to effectiveness of data transmission and communication with robotic systems. The naming mode in the DIPS affected the efficiency and scalability of the overall BCI technology intelligence system. Naming in the DIPS was the process of assigning characters to EEG artefact or EEG data as an entity in the intelligence system [**179**]. To access EEG data as an entity, addresses defining the access point were used. In ensuring that addresses were unique and true identifiers, the naming of the EEG artefact consisted of the following properties:

- Each identifiers used in the EEG artefact identification process referred to one EEG artefact as an entity.
- Each of the entities were associated to and referred to by one identifier
- The identifier always referred to the same entity.

By using specific identifiers in the EEG artefact identification process, EEG entities were unambiguously referred to. Addresses on the other hand may not be used as identifiers as they can be assigned to different EEG data entities.

6.7 EEG Data Synchronisation in DIPS

Data synchronisation across different EEG platforms was usually difficult as each system had its own proprietary data management and transmission system. As such data transmissions in distributed systems were faced with the same challenges. One of the many challenges was the in clock synchronization across the different EEG platforms as the importance of time varied from system to system. Developing real-time EEG data synchronisation required the use of external clocks which were desirable. The clocks increased data transmission efficiency and removed redundancy. Synchronisation amongst the clocks remained an issue in the data transmission to end effectors.

Considering the data transmission between EEG headset and the robotic system controlling a prosthetic arm, the delay or the time offsets existing between the EEG headset and the prosthetic arm motion was modelled as:

$$\delta = \frac{(T_2 - T_1) + (T_4 - T_3)}{2} \tag{6-2}$$

Where T_1 represents the time EEG headset send the transmit data request, T_2 represents the time of EEG data receipt at the prosthetic arm recorded by the microcontroller controlling the arm, T_3 represents the time record return stamp issued by the microcontroller at the prosthetic arm, T_4 represents time of arrival of the record stamp from the prosthetic arm. The minimal value buffered from eight pairs of time stamps between the EEG headset and the prosthetic represents the best time estimate for the delay between the two systems.

Since more portable EEG data was transmitted wireless from the headset to the computer, BCI system clock synchronization using reference broadcast synchronization ensured that clock synchronisation was achieved internally by synchronising the end effectors and EEG signal receivers. Considering the EEG headset as the system comprising of many electrodes forming a suitable sensor network; the time required to transmit EEG signal was fairly constant given that there are no multi-hop routing of EEG data. The data transmission inception was regarded as the time the EEG signal leaves the wireless network interface of the EEG headset. The consequence of this procedure eliminated critical sources for EEG data transmission variation as their relevance diminished in the estimation of time delay in EEG data transmission. The time required to construct the bioelectric message and the time spent on the EEG neural network in accessing the data played minimal role in the reference broadcast synchronisation system. In the reference broadcast synchronisation system, EEG electrode broadcasts the reference bioelectric message m, and the time $T_{\rho,m}$ for each network node ρ as it received the bioelectric message m was measured from the local clock of the network node [**179**]. Disregarding skew in clock readings, two network nodes can exchange data arrival times in order to estimate their mutual relative offsets modelled as:

$$Time\ Offset\ [p, q] = \frac{\sum_{k=1}^{M}(T_{p,k} - T_{q,k})}{M} \tag{6-3}$$

Where M represents the total number of reference broadcast messages sent.

6.8 EEG Data Dependability and Reproduction

Critical to the distributed intelligence processing system was the reproduction of EEG data and artefact. The effective replication of EEG data in the DIPS enhanced EEG data reliability and enhanced BCI technology system performance. The issue considered in the development of the DIPS was the consistency of the EEG data and artefact. Real-time updates of EEG data and artefact classifications were critical to deployment of robotic motions. Consistency required that EEG classifications were updated regularly. The synchronisation of all EEG data models can be necessary given that it was the price to pay for lower system performance. Consistency of EEG data can be resolved using continuous consistency model, sequential consistency models or causal consistency models. Sequential and causal consistency models can be applied to the level of EEG data read and write processes. It was noteworthy that process synchronisation in the DIPS can be associated to different synchronization variables [**179**]. In synchronising DIPS processes, various operations can simultaneously synchronise their activities nonexclusively under the following conditions:

- Each operation acquired access by the DIPS process having the data synchronization variable was not allowed to execute with respect to the given process until all EEG data updates to the protected shared intelligence have been performed with respect to that process.
- Before the initiation of the exclusive mode process, access to the synchronisation variable by the specific process was permitted in accordance to the requirements of the process. No other process may engage the synchronisation variable even in nonexclusive mode.
- After the initiation of the exclusive mode, access to the synchronisation variable by the other processes and nonexclusive mode processes may not be permitted until the executive of the exclusive mode operation with respect to the synchronisation variable.

In using synchronisation variable in EEG data consistency, data associations can be accessed explicitly by middleware and sub intelligences systems.

6.9 Fault Tolerance in the DIPS

Fault tolerance was the ability of the DIPS to handle failure resulting from the absence of EEG data or unbounded EEG frequency data. Fault tolerance in the DIPS referred to the dependability of the DIPS. The dependability of the DIPS required that the DIPS have the following properties embedded in it. These are availability, reliability, safety and maintainability. The availability of the DIPS referred to the readiness of the DIPS to be used immediately. Often system readiness may not be trivial in complex mechatronic system. The availability of the DIPS provided the opportunity or the probability that the full BCI technology was functioning adequately. High level availability of the DIPS implied that the BCI system can be functional at any given time.

Reliability of the DIPS implied that BCI technology can function continuously without failure. The dissimilarity with availability was that reliability was measured with respect to time interval while availability was measured with respect to instant in time. High reliability of DIPS was the status that implied that the BCI technology can continue to function without interruption for a relatively long period of time. Given that the autonomic wireless EEG network may use point to point connection, communication failures resulting from the abrupt termination of the wireless connection in the autonomic wireless setup. The masking of communication crashes, arbitrary failures and omission failures can ensure that fault tolerance capability of the DIPS was focused on faulty processes rather than unmasked failures [**179**].

6.10 Security in the DIPS

Data security was very important in the transmission of EEG across the DIPS. Data security, though important in the overall structure of the DIPS needed to be passive in its functionality. EEG data security policies ensured that communication between processes and the technology user enforced accurately. In order to ensure that communication and EEG data integrity was not compromised, secure channel was used in the communication processes and data transmission. This reduced and most probably eliminated the possibility of data leakage. The security in the DIPS related to the dependability of the EEG data in serving as source signals for robotic motion controls. Threats to EEG data include interception of information derived from EEG data, interruption of EEG data generation, modification of information derived from EEG data and fabrication of information from EEG data. Keeping at bay these threats ensured that the security profile of the DIPS was at optimum level. The security mechanisms necessary in ensuring that the security profile of the DIPS remained at optimum level included: EEG data encryption, authentication, authorization and auditing [**179**].

6.11 Summary

The integration of neuro-sumbolic behaviour language architecture into the development of BCI system, introduced the desired flexibility in associating mechatronic and robotic system control codes to the cognitive states of human beings. In order to ensure that the selected cognitive state reflected the intended robotic motion execution, EEG artefacts were tagged using neuro-symbolic tagging system and the information transmission and coordination across the EEG neural network was managed using the distributed intelligence processing system. The distributed intelligence processing system also facilitated the effective implementation of the neuro-symbolic language synchronisation, fault tolerance, EEG data reliability and dependability in ensuring that the security profile of EEG data was not lost.

Sensor sampling rates and the actions performed by the robotic systems in response to the sampling rates were identified as trade-offs. The faster the sampling rate, the more reliable and accurate the sensorial data even in the midst of computational overflows. Slower sampling rates on the contrary caused the robot to behave and exhibit inappropriate behaviours and motion movements. Sensory architecture exhibiting slower sampling rates may induce very slow reaction time of the robot in the dynamic environment. The mapping of the brainwave to determine the source of its sensory network allowed for the determination of the motion cognition. The neurons in the brain were assumed to be in charge of the motion actions in the experimental tasks of controlling robots using brain signals. They were associated with different areas in the brain without questioning the difference in behaviour or response of the robot at a level of the quantity of neurons that are present in each area of the brain. The brain for experimental purposes was assumed to be a distributed intelligent processing system (DIPS) which was formed through the collection of loosely interactive special neuronal nodes, where each node specialised in data collection, motion inducers, data communication and acted upon the environment through the control of robotic devices. The work presented in chapter 6 was performed in order to develop a specialised behaviour-based robotic hand control system which reacts to EEG artefacts.

CHAPTER SEVEN

Applications of EEG Artefact Identification, Extraction and Classification Technology

In this chapter, the practical implementations of the study and applications of EEG data identification, extraction and classifications in controlling the robotic hand with dynamic system complexities is presented and discussed. The other applications showcased in this chapter include possible semi-autonomous systems and mechatronic system integration with the developed system. The chapter provided valuable information in multiuser detection and communication strategy, cognitive management, mental work load management, use of EEG data in marketing and advertisements, semi-autonomous computing services, vehicular applications and hybrid flexible automated robotic systems. The specific contribution and application of interest implemented in the study is the control of the robotic hand using the models proposed in chapter 3, chapter 4, chapter 5 and chapter 6. The applications presented in sections 7.3 to 7.13 are applications which can also be implemented using the integrated model proposed in chapter 5. The proposed model are implemented in the applications using customized software abstraction. The applications are expansions to the study and are not limitations to the study.

7.1 Introduction

The robotic hand BCI translated EEG signals into action commands by reading EEG signals from an array of neurons and using specialised computer programs for analysis and interpretation. The different mechanisms that facilitated the process of signal transmission and interpretation were grouped into different processes. The grouped processes include EEG signal recording, the type of mental strategy, the mode of operation, feature extraction and classification and the type of feedback mechanism that was employed in the robotic hand BCI system. The mechanics of the interface systems of the robotic hand BCI system introduced one of the biggest challenges that were faced in the development the robotic hand BCI technology.

The recording of electroencephalographic signals required that two phenomena be identified in the initiation of the signals. The phenomena were in the area of identifying if the signals were purely event-related potential changes or on-going event-related potential changes. The event-related potential variations may be evoked potential or slow cortical potential shifts in the brain waves. Event-related variations in on-going EEG recordings in specific frequency bands can be referred to as event-related de-synchronisation or synchronisation of brainwaves during the recordings. The mental strategy necessary for robotic hand BCI organisation was the methodology that defined the technique employed by the robotic hand user to modify bioelectrical activity in the brain. The condition of operation of the robotic hand user, motor imagery strategies and focused visual attention provided useful control options for the robotic hand user. They allowed the robotic hand user to have control over specific components of the oscillatory activity in robotic hand BCI system.

7.1.1 The Robotic Hand Functional Requirement

The BCI architecture controlling the robotic hand was designed to detect EEG signal from the brain and translate that information into an open control system. The open control system reflected the thoughts and intentions of the user's brain. The robotic hand BCI system was made to decode electrophysiological signals that were representations of motor intent in the brain. The robotic hand BCI architecture required that the user must have fully functional cognitive system and may not have motor impairment. The robotic hand is shown in figure 7-1. The robotic fingers were controlled using geared DC motors. For accurate positioning and turning, the wrist of the robot hand is controlled using servo motors. In summary the robotic hand BCI architecture accomplished the following functions:

- The robotic hand BCI architecture was capable of full or partial decoding of human intentions from brain activity alone.
- The robotic hand BCI architecture provided completely new path for information transmission from the brain using augmented wireless autonomic network technology.
- The robotic hand BCI system changed electrophysiological signals, EEG rhythm or neural firing rate from the reflection of brain activity into robot control commands.
- In certain applications, the system can be used to replace muscles and nerves. The system can transmit equivalent electrophysiological signals and convert the signals into robot motion.

Figure 7-1: The Robotic Hand

7.1.1 Robotic Hand BCI- Operation Mode and Feedback Type

The robotic hand BCI system mode of operation was defined when the user was about to perform mental tasks or intend to transmit EEG data wirelessly using the autonomic network. The distinct modes of operation of the robotic hand system can be cue-based or computer-driven asynchronous mode of operation. The cue-based asynchronous mode of operation used an externally driven activation system. The second mode of operation was the un-cued, user –driven asynchronous BCI mode of operation. The user-driven asynchronous mode of operation used an internally driven activation system.

Feedback types employed in the training sessions, application, implementation and deployment of the robotic hand BCI system were important components in the organisation of the robotic hand BCI system. The robotic hand BCI system feedback may be discrete, continuous, virtual, realistic, or represented in ID, 2D or 3D. The combination of the feedback system and the robotic hand BCI system into one system formed the closed loop system of two adaptive controllers comprising of the brain and the computer.

7.1.2 The Significance of Robotic Hand BCI to the Human Race

Advancements made and on-going researches in the development of BCI technology have shown to be of high importance to both healthy subjects and physically challenged subjects. Researches made in BCI development at various stages have been implemented and tested using healthy subjects as end users. Examples of such implementation strategy of the BCI technology include healthy subjects using their minds for navigation while their hands are busy with other motion actions. NeuroSky and Emotiv have developed EEG headsets that can allow healthy subjects to engage their minds in the control of specific tasks.

Healthy subjects may have the need to communicate to world around them in situations where normal or conventional communication interfaces are unavailable, inadequate or too demanding. The interactions may require several actions to be executed at the same time. Fighter pilots, soldiers, surgeons, drivers, mechanics, technicians, and cell phone users may experience some form of induced disability. Induced disability includes situations where the voice or hand mode of communication may be unavailable and unrealistic. Using robotic hand BCI technology at such scenarios can provide way of assisting such individuals to access information, and perform difficult tasks. An example is in playing games where the gamer may require several keys to execute an action in the game.

The integration of other technologies such as wireless technology and Bluetooth technology into the robotic hand control system facilitated the creation and development of robust wireless BCI system. The use of wireless technology system in the robotic hand BCI system increased the usability, accessibility and user convenience level. The acceptance level increased robotic hand BCI system usage to the level of common electronic usage, hardware integration and management. The integration of wireless technology into robotic hand BCI system facilitated the transmission of information with ease. The type of embedded system and technologies used in the control of the robotic hand BCI system and conventional communication interfaces differ significantly. The differences were in the desired outputs and effects expected from the robotic hand BCI system. The robotic hand BCI system can be programmed to achieve particular tasks while imagining different body motions or actions. The body motion include as hand movement or leg movement while trying to pick up an object etc. Software development can allow for easy use of mental activities that are readily available and may require less training session [**70**].

The robotic hand BCI system was suited for certain tasks and mind activities just like conventional communication input devices such as the keyboard are suited for typing letters. Software development increased the versatility and usage of robotic hand BCI system such that the robotic hand BCI system formed a closed loop control of its actions and activities. The advancements made in robotic hand BCI software development have allowed for the general assessment of human alertness, frustration, exhaustion, comprehension, engagement, focus and attention. These assessments assisted in the development of robust and adaptable robotic hand BCI system that can be adapted to each user. Specific motor activities can be achieved by training normal subjects to produce specific brain activity. Carrying out several trainings and producing specific brain activities can lead to the improvement of body movement components. This can provide valuable methods for rehabilitating physically challenged subjects. The use of physical communication interfaces may be porous to eavesdropping simply by observing the applicable motion movements and signatures. The advancements in BCI technology may provide one of most secured way of transmitting information from the brain to an electronic device. The confidentiality of information passage and security can be some of the advantages healthy subjects can derive from the use of BCI technology.

7.2 Application 1: Robotic Hand Control Results

The robotic hand provided solutions and assistive functions that were complimentary to the activities performed by human beings. Well-developed robotic hand system can provide the sophistication and function needed by the user provided they are well defined prior to use. The robotic hand BCI provided strategies of communication through nonverbal means. An integral collaboration with users having vocal challenges can be achieved through using robotic hand BCI technology. The steps taken in implementing the models discussed in this thesis on robotic hand system are presented in this section. In figure 7-2, the ICA was computed using the 14-channel Emotiv electrode. The number steps taken to complete each channel analysis are also shown in figure 7-2. The signal covariance differed from the identity EEG signal by 3.33.3067e-15.

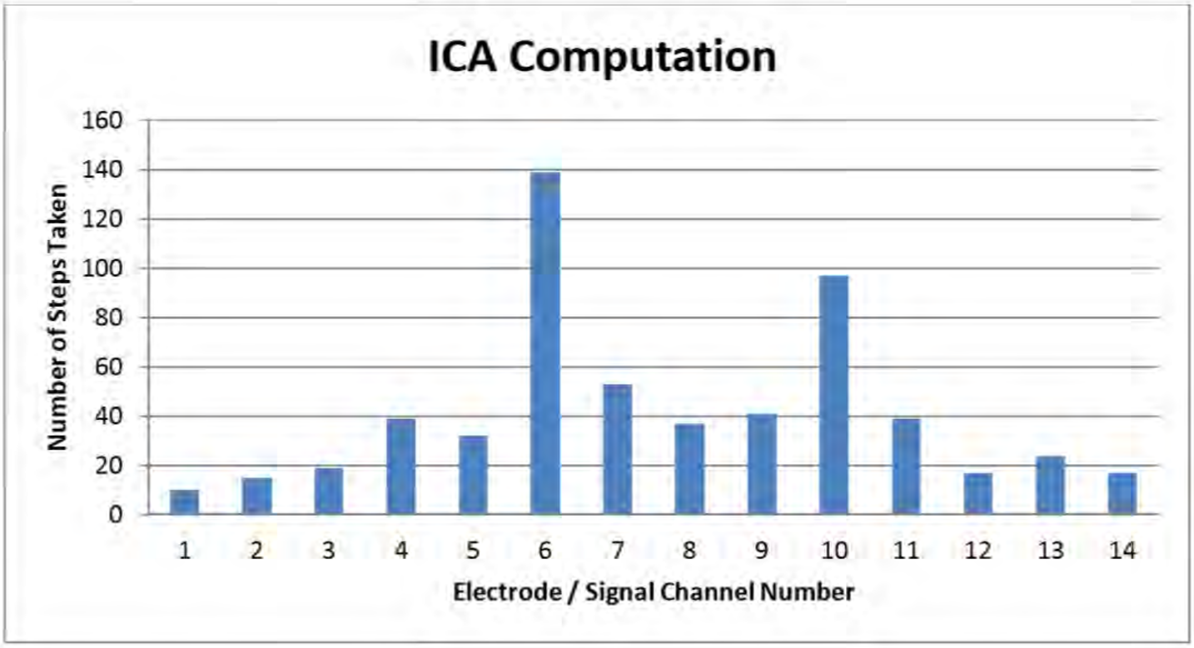


Figure 7-2: 14- Channel Independent Component Analysis Computation

In clustering the EEG artefacts, as indicated in table 7-1, the total sum of distances from the signal cluster centre was 854.708.

Table 7-1: EEG Signal Clustering

EEG Signal Channel	Number of Iterations	Total Sum of Distances from Cluster Centres
1	18	861.257
2	6	861.937
3	14	854.708
4	10	858.606
5	12	862.024

In implementing the RBF system discussed in section 5.3 of chapter five, the RBF system goal was set to achieve 0.007 MSE. The system performance was 2.80369e-11. The system converged after using 150 neurons to achieve system goal. The results are indicated in figure 7-3.

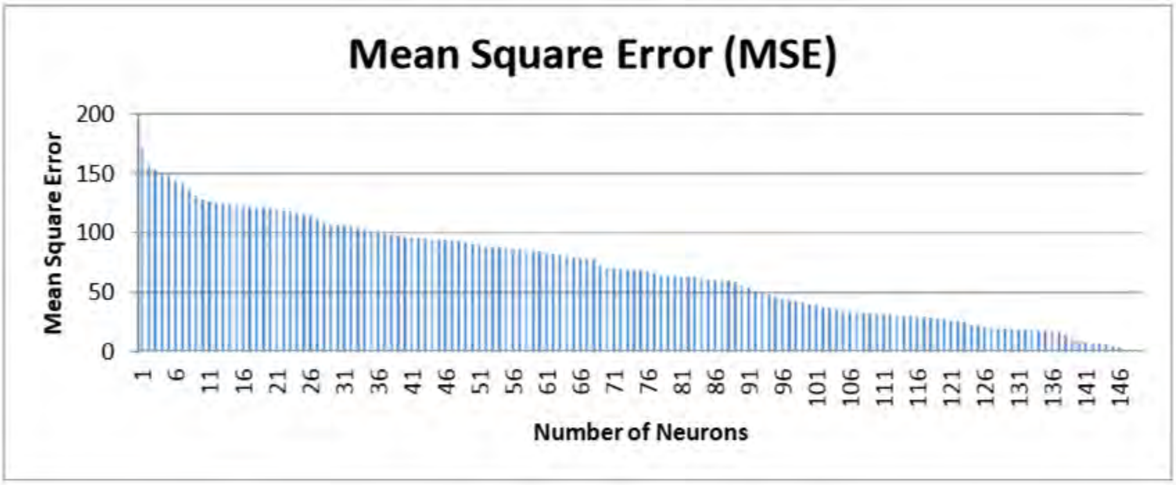


Figure 7-3: Investigating System Performance from MSE

The principal component analysis results are shown in figure 7-4. The PCA reduced the EEG signal to manageable data format while retaining the key components of the EEG signal

$$\begin{bmatrix} 0.0215 & -0.0830 & 0.9963 \\ 0.4791 & 0.8755 & 0.0626 \\ 0.8775 & -0.4760 & -0.0586 \end{bmatrix} \begin{bmatrix} 0.0239 & -0.0728 & 0.9971 \\ 0.4719 & 0.8801 & 0.0529 \\ 0.8813 & -0.4692 & -0.0554 \end{bmatrix} \begin{bmatrix} 0.0244 & -0.0811 & 0.9964 \\ 0.5044 & 0.8616 & 0.0578 \\ 0.8631 & -0.5011 & -0.0619 \end{bmatrix}$$

Figure 7-4: First, Second and Third Principal Components Matrix

In the PCA algorithm, the first and second matrix represented the desired components of the EEG data. In order to ensure that all the EEG data were well represented, only the first and second principal components were used. The results are indicated in table 7-2.

Table 7-2: PCA Performance on First and Second Components of EEG

PCA 1 (%)	PCA 2 (%)
16.5	15.8
16.1	14.7
17.5	16.2
17.7	16.3
18.6	15.2
17.2	15.3

The EEG data was screened in order to determine the signal channel mean and signal skewness. The results are shown in table 7-3.

Table 7-3: EEG Signal Channel Statistics

Channel Number	Mean	Trimmed Mean	Median	Standard Deviation	Trimmed Standard Deviation	Skewness
1	3.40	1.47	0.801	33.95	19.82	4.15
2	0.534	0.901	0.889	23.18	15.20	0.992
3	3.58	2.97	2.14	25.42	20.75	0.761
4	3.55	3.10	2.30	25.11	20.81	0.561
5	4.23	3.64	2.64	25.18	20.51	0.73
6	2.03	1.59	1.24	21.71	17.40	0.755
7	3.26	2.84	1.94	21.70	17.94	0.56
8	3.49	3.24	2.61	24.53	20.84	0.271
9	2.94	2.73	2.36	25.90	21.86	0.224
10	3.54	3.24	2.68	18.25	15.05	0.623
11	2.41	2.35	2.07	16.54	13.81	0.861
12	2.87	2.70	2.36	22.78	19.41	0.188
13	2.89	2.81	2.46	20.87	17.88	0.12
14	3.76	3.65	3.22	23.96	20.53	0.134

The signals were averaged using appropriate window functions. The windowing functions that can be used are rectangular, Hanning and Blackman-Harris windowing functions. The research aim was not to compare the effectiveness of each windowing function. Hanning windowing function was used to smoothen the EEG signal before the power values were average. In order to compute the power values, each EEG frequency band was isolated. The average power values are shown in table 7-4. The averaged signal power values were used to control the motion of the robotic hand. The averaged power values are functions of the signal correlation values. The EEG signal correlation values were instrumental in the developing the control strategy for the robotic hand. The correlation values were passed from the Emotiv test bench to the Open Sound Control (OSC) interface. These values are indication of cognitive actions that were used to control the robotic hand. Further steps taken in developing the robotic hand BCI system is shown in figure 7-6. The results, feedback and the robotic hand performance monitoring control system are indicated in figure 7-7, figure 7-8, figure 7-9 and figure 7-10. The robotic hand was driven by geared DC motor for speed and servo motors for position and control. In order to achieve motion and position control, the user was trained on how to activate specific EEG artefact and robot command using Emotiv control panel and Test bench. The EEG artefact was then passed on to the Mind Your Open Sound Control (OSC) interface which can be assessed by the programming environment known as the Processing software. The artefacts were identified through the averaged signal power values as shown in table 7-5. The programming environment assessed the EEG artefacts using specific addresses and libraries shown in table C-1 in the appendix section. The desired thresholds were set on the programming environment. Two wireless transmission options were investigated and used.

Table 7-4: EEG Signal Power Correlation Values

Time (seconds)	Signal Correlation Coefficient	Meditation Level	Attention Level
18-19	0.835	95	69
19-20	0.938	80	88
20-21	0.839	85	65
21-22	0.949	83	70
22-23	0.745	70	57
23-24	0.749	79	69
24-25	0.681	90	55
25-26	0.994	99	68
26-27	0.681	91	68
27-28	0.735	74	79
28-29	0.699	78	60
29-30	0.930	85	78
Average Power Spectrum	0.815		

Table 7-5: Correlating Robot Arm Motion with Average EEG Signal Power Values

COGNITIVE ADDRESSES	ROBOTIC MOTION EXECUTED	AVERAGE SIGNAL POWER VALUE
/COG/PUSH	EXTEND THE ROBOTIC ARM FORWARD	0.993272
/COG/PULL	RETRACT THE ROBOTIC ARM BACKWARDS	0.921329
/COG/LEFT	ROTATE THE WRIST TO THE LEFT	0.818182
/COG/RIGHT	ROTATE THE WRIST TO THE RIGHT	0.636364
/EXP/WINK_LEFT	MOVE THE ROBOTIC ARM TO THE LEFT	0.818182
/EXP/WINK_RIGHT	MOVE THE ROBOTIC ARM TO THE RIGHT	0.727273

The performance of the proposed EEG artefact extraction and classification model was evaluated against the RBF, WPT, LVQ, LVD, LR, Bayes, PCA, LDA and ICA. The proposed model was the embodiment and augmentation of all the aforementioned models. Each of these models have their specified function as discussed and explained in chapter five. Figure 7-5 illustrates the performance of the sub-models and the proposed model. The proposed model was found to have 91.32% accuracy in its functional capacity. This result was the combinatory effect of the models in the proposed model.

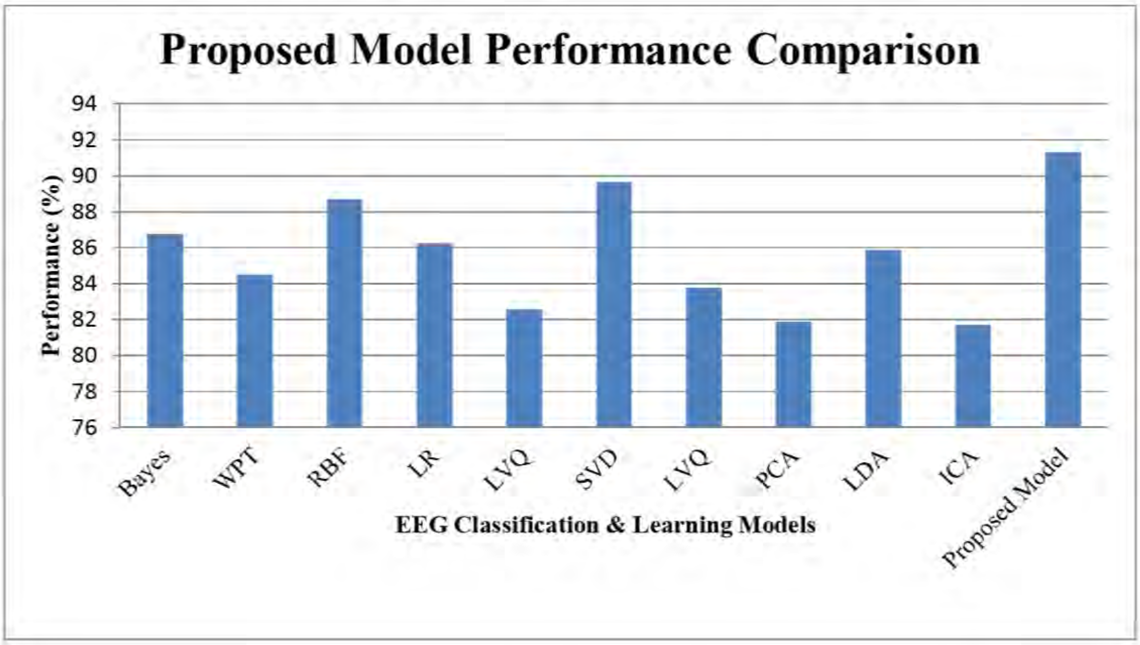


Figure 7-5: Proposed Model Performance Comparison

For long range and wider coverage the RN-171-XV wireless modules was used and for short range and line of sight motion control application the X-bee-Pro wireless Module was used. The robotic arm motions that were tested include extending the robotic arm forward, backwards, rotating the wrist to the left and to the right as illustrated in figure 7-7, figure 7-8, figure 7-9 and figure 7-10. The blue square box in the visual feedback system moved from left to right and right to left in response to robotic motions executed. The horizontal coloured bars having colours light green, red, light blue and purple increased from left to right in response to the set system threshold. The colours appeared when the threshold was reached else they turned blue. The sensitivity of the system was also controlled using the system threshold. During the tests, the threshold was set at 0.5. Increasing the threshold value implied an increase in the time required for the robotic arm to receive motion command and vice versa. The tasks that were being executed were displayed on the top right corner of the feedback system. The robotic arm motions were executed using the addresses indicated in table 7-5 and table C-2. Visual feedback system shown in figure 7-7, figure 7-8, figure 7-9 and figure 7-10 was used to monitor the response of the proposed system. This feedback was used in validating the integrative model proposed in the study.

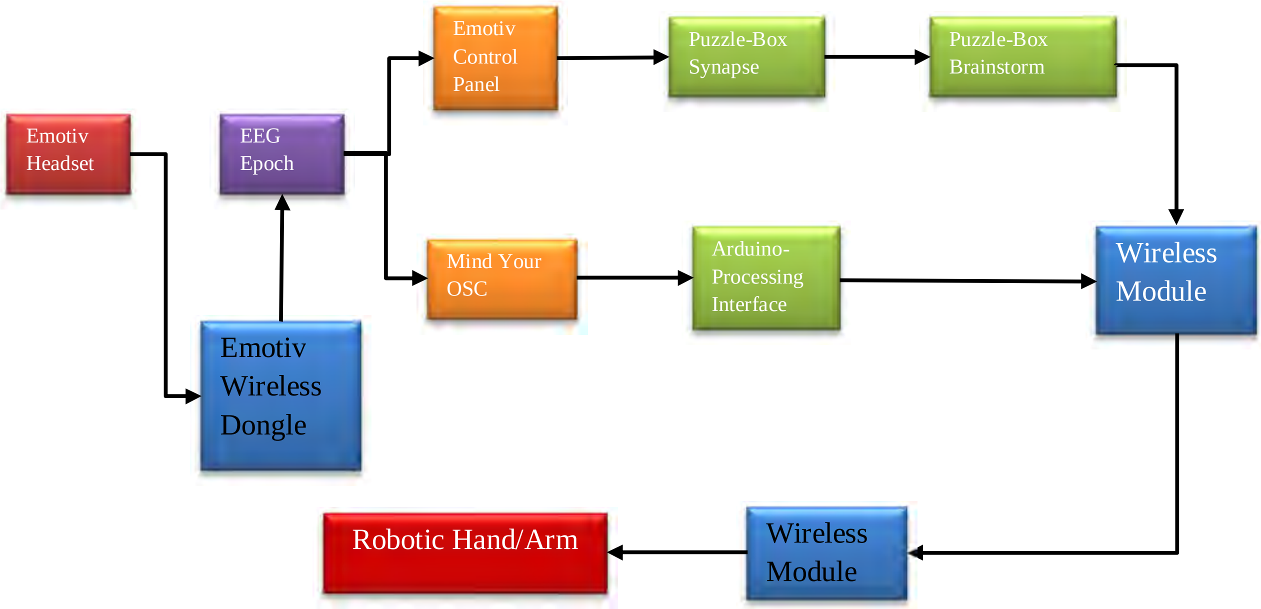


Figure 7-6: Robotic Hand Control Structure using Emotiv Headset

Figure 7-7: Robotic Hand Extending Forward

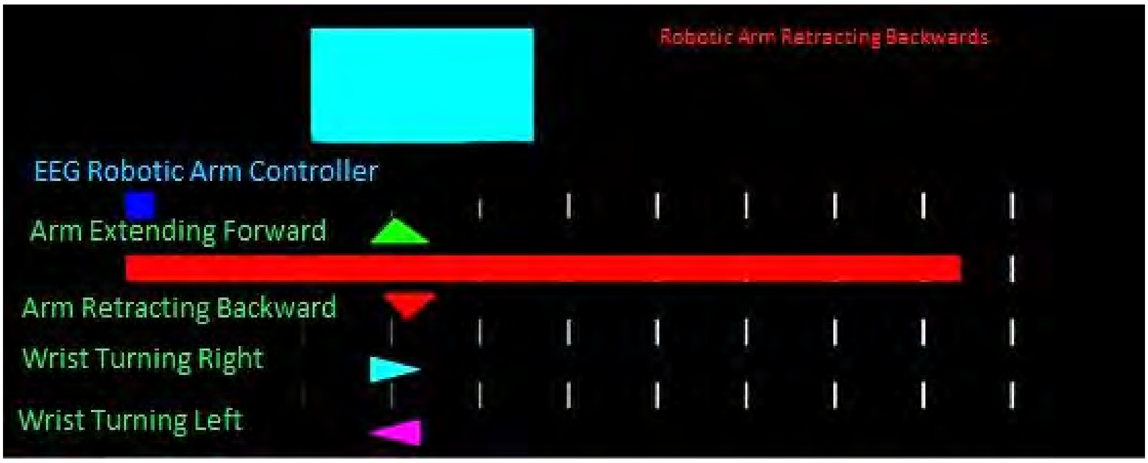


Figure 7-8: Robotic Hand Retracting Backward

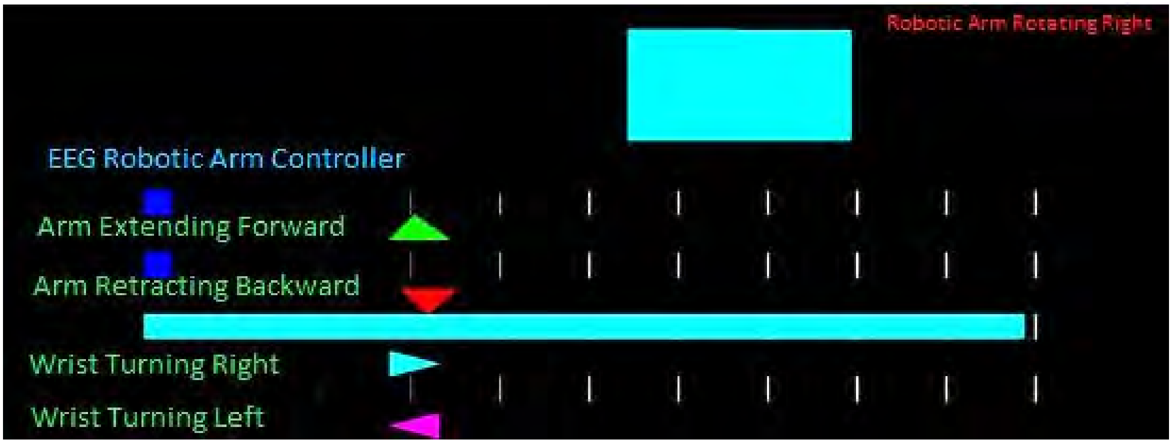


Figure 7-9: Robotic Hand Rotating to the Right

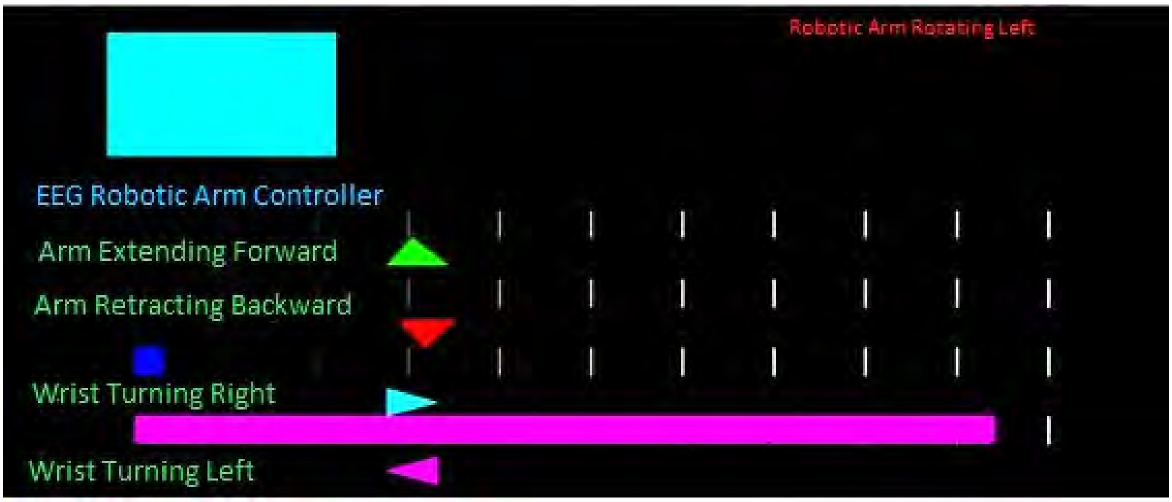


Figure 7-10: Robotic Hand Rotating to the Left

The EEG power signal correlation results were functions of the FFT performed on the EEG signal as each motion was being executed. These are presented as spectral power density values. In figure 7-11, the EEG signal power-frequency relationship is shown for the robotic hand retracting backwards. As shown in figure 7-11, it can be seen that the robotic hand retracting backwards has an average power value of -9.082 dB/Hz. In figure 7-12, the power-frequency relationship for the robotic hand extending forward is shown. As indicated in figure 7-12, it can be observed that extending the robotic hand forward has an average power value of -7.515 dB/Hz. In figure 7-13, the power-frequency relationship for rotating the robotic hand to the left is shown. As illustrated in figure 7-13, turning the robotic hand to the left has an average power value of -15.019 dB/Hz. In figure 7-14, the power-frequency relationship for rotating the robotic hand to the right is shown. It can be observed that rotating the robotic hand to the right has an average power value of -12-983 dB/Hz. The EEG power spectral densities were computed using the EEG Alpha, Beta, Gamma and Theta frequency bands. The peridogram of the EEG signals yielded an average power spectrum of 0.815 as indicated in table 7-4. The robotic hand motions were mapped to the EEG frequencies which were associated to the specific cognitive task of interest to the user. The distinct comparison between the executed motions was that the robotic hand should perform motions mapped with specific cognitive tasks.

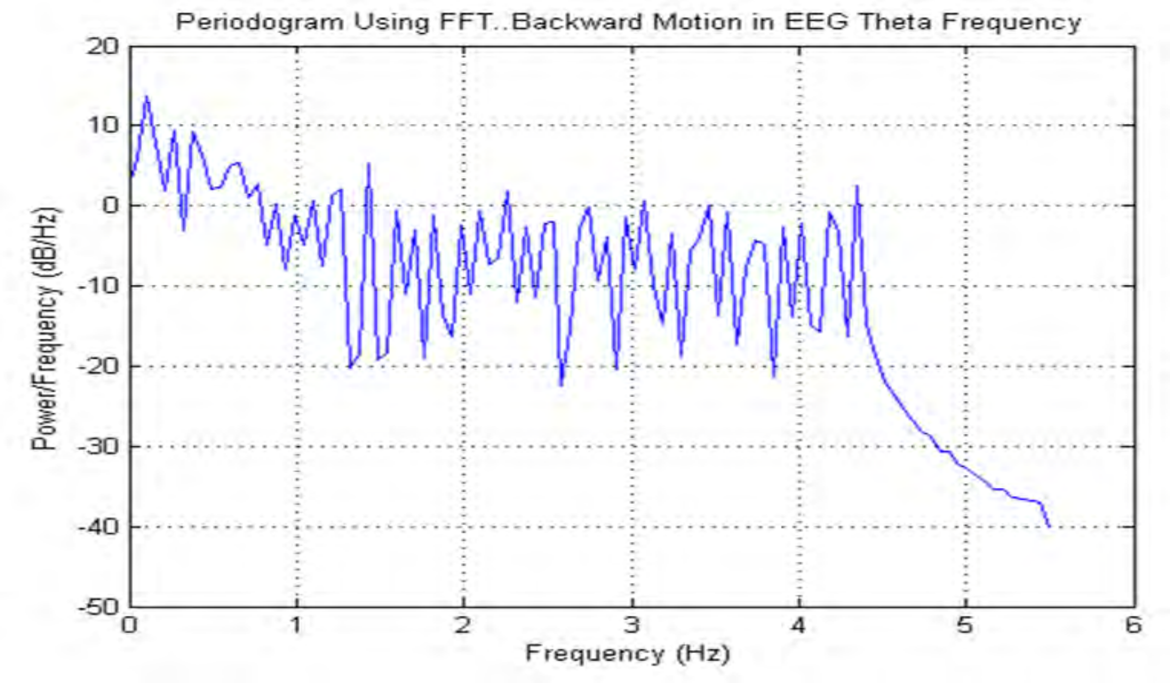


Figure 7-11: EEG Spectral Power Result – Robotic Hand Retracting Backwards Motion

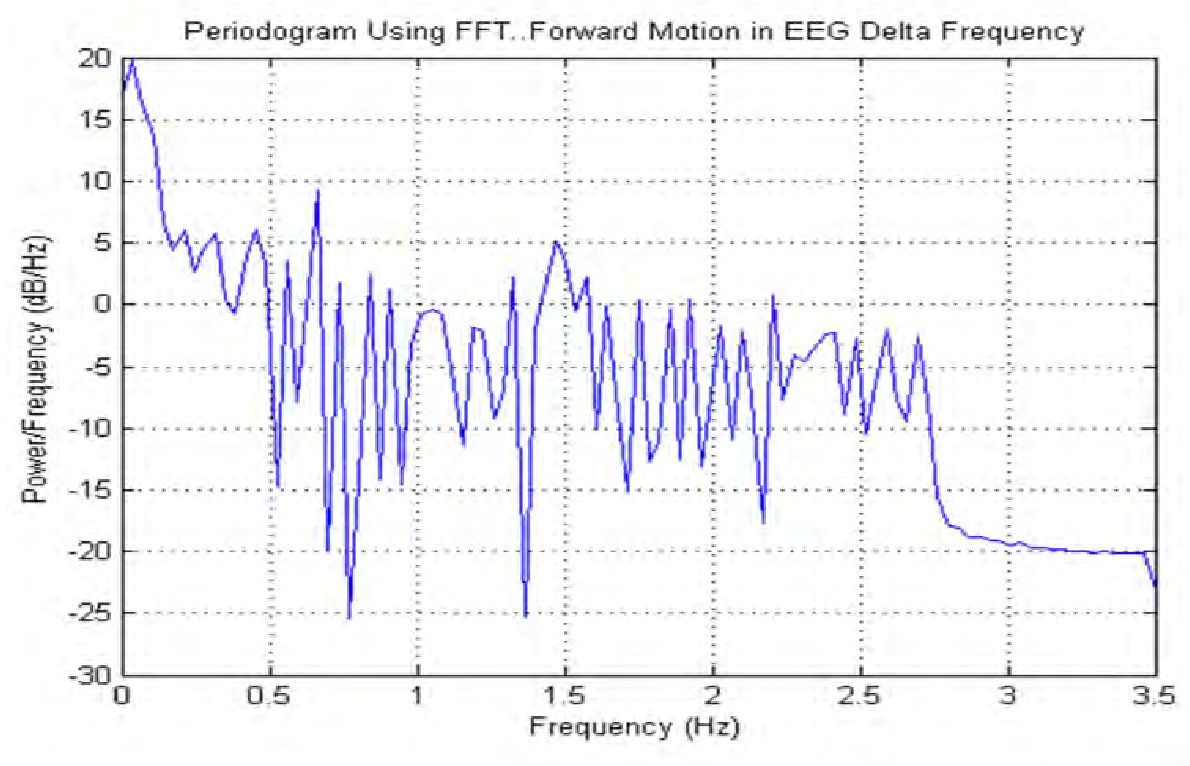


Figure 7-12: EEG Spectral Power Result – Robotic Hand Extending Forward Motion

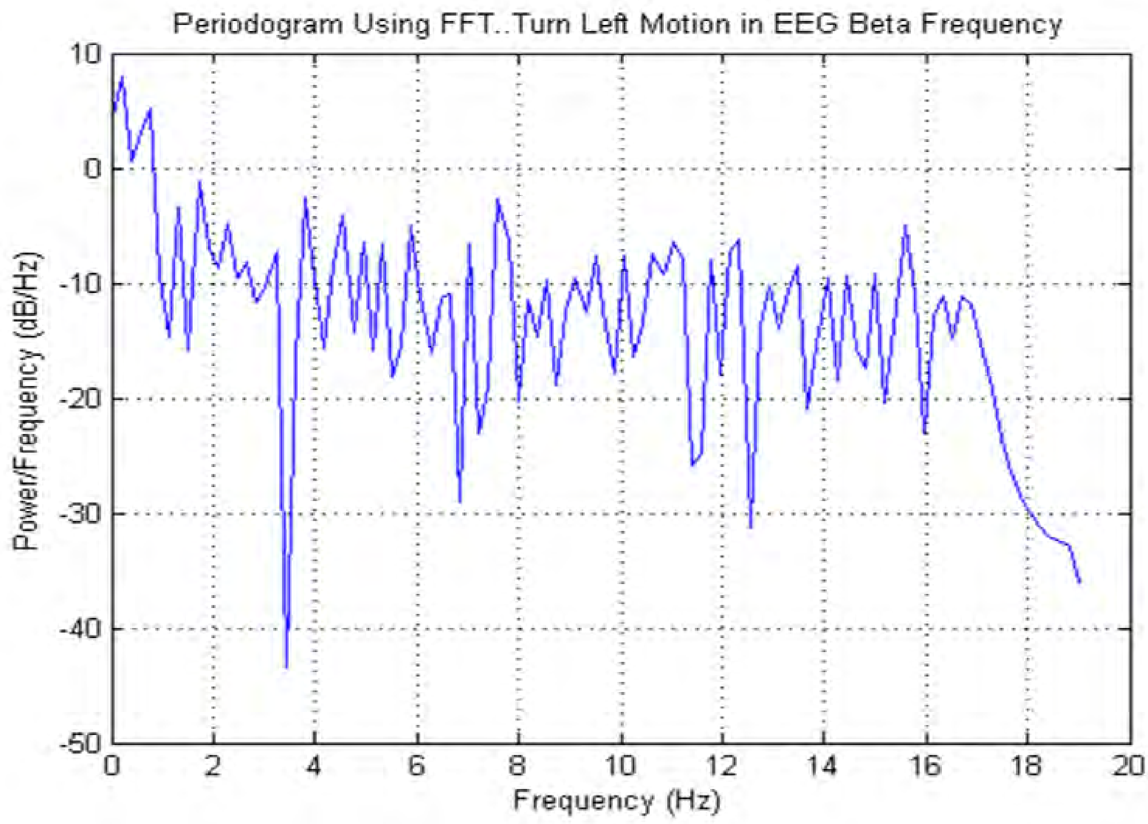


Figure 7-13: EEG Spectral Power Result – Robotic Hand Rotating Left Motion

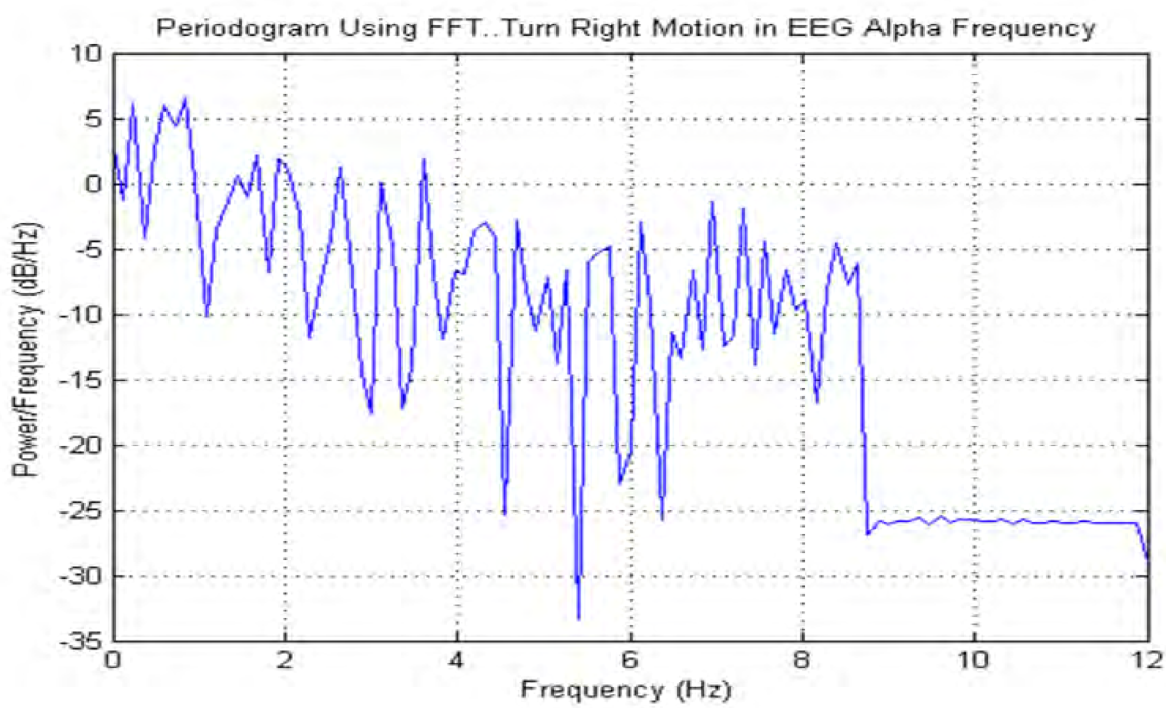


Figure 7-14: EEG Spectral Power Result- Robotic Hand Rotating Right Motion

7.3 Further Applications of EEG Artefact Identification, Extraction and Classification Technology

Further applications of EEG artefact identification, extraction and classification are proposed and presented in this section. The applications can further be developed beyond the level presented in this thesis.

7.3.1 Application 2: Multiuser Detection and Communication

The EEG analysis methods discussed so far were essential in separating the information and communication among different subjects trying to transmit the same meaning to the robotic device. ICA played an important role and was integrated in creating multiple access communication scheme for different subjects transmitting EEG signals in a given environment or space. The primary objective of the EEG multiple access system was to enable each subject to transmit EEG signals irrespective of other EEG transmissions from each individual most possibly simultaneously. This was achieved through training the software to recognise the frequency pattern of each individual transmitting the EEG signals. The translation of human intentions into visible actions was possible and became the reality of present day technology The multi-user detection and communication platform was investigated using the RN-171-XV wireless Module shown in figure A-1 in the appendix section. The system implementation can be used with either the models shown in figure 7-6.

7.3.2 Application 3: Mental Workload Management

Metal workload in high levels creates stress and dysfunctional work behaviours an environment filled with complex control systems and control commands. For example technicians working in the machine workshop were monitored for half an hour. The performance monitoring of each individual at various intervals were critical in maintaining optimum operational conditions. High metal workload and stress can lead to operational failures. The consequences of such failures may lead to catastrophic activities. Human performance decline can be as a result of under stimulation and work overload. In measuring accurately the EEG signals, additional information known as the mental workload of individuals are encoded in the EEG signal. This was a critical application in maintaining the safety of individuals working in the workshop and in the advanced flexible manufacturing environment. The technicians are faced with various machine operations while using advanced flexible manufacturing equipment. The brain is multitasking in controlling and monitoring various automated systems in the manufacturing environment. Sustained vigilance of workers in the working environment was regarded as important criteria in maintaining efficiency of the overall manufacturing environment.

The relationship between observed EEG signals and the mental workload of the workers revealed the level of vigilance, level of expertise and task performance of the individual in the manufacturing environment. The investigation results were monitored using the interfaces shown in figure D-1, figure

D-5 and figure D-6. Accurate monitoring of the mental workload prevents operational and technical errors and this could be achieved through timely interventions and the prediction of human performance decline through the monitoring and analysis of EEG signals. The development of EEG monitoring systems provided adaptive systems can send out alerts when there was performance decline in workers. Timely intervention required in the manufacturing environment that ensured and sustains the safety of workers was provided using the EEG monitoring system. Feedback on the mental work load management system was monitored as illustrated in figure 7-15.

7.3.3 Application 4: Cognitive Strategy Management

The management of human cognitive system is critical in improving throughput in manufacturing environment. Memory improvement and cognitive biases are form factors in choosing and making suboptimal decisions that may affect productivity in the manufacturing environment. EEG data analysis reveals that memory performance and improvement through self-appraisals could be one of the determining factors that contribute to humans choosing an optimal strategy in the manufacturing environment. High level cognition and strategy formulation in the manufacturing environment is critical in making effective decisions that increase productivity. Given that there are many ways of improving human memory; modelling and predicting brain activity through EEG data analysis provides the individual with ways of making choices and strategies that are productive and assists in identifying counterproductive or suboptimal strategies in the manufacturing environment. EEG data analysis indicated that behavioural performance appraisal can be performed memory usage strategy management. EEG signals can be used to identify the social factors that exist when there are social interactions and general interactions between humans and machines. The cognitive strategy management was investigated using the Neurosky EEG headset and while monitoring the E-sense level, concentration and relaxation levels as shown in figure 7-15. The model illustrated in figure 7-16 is the architectural setup for figure 7-15.

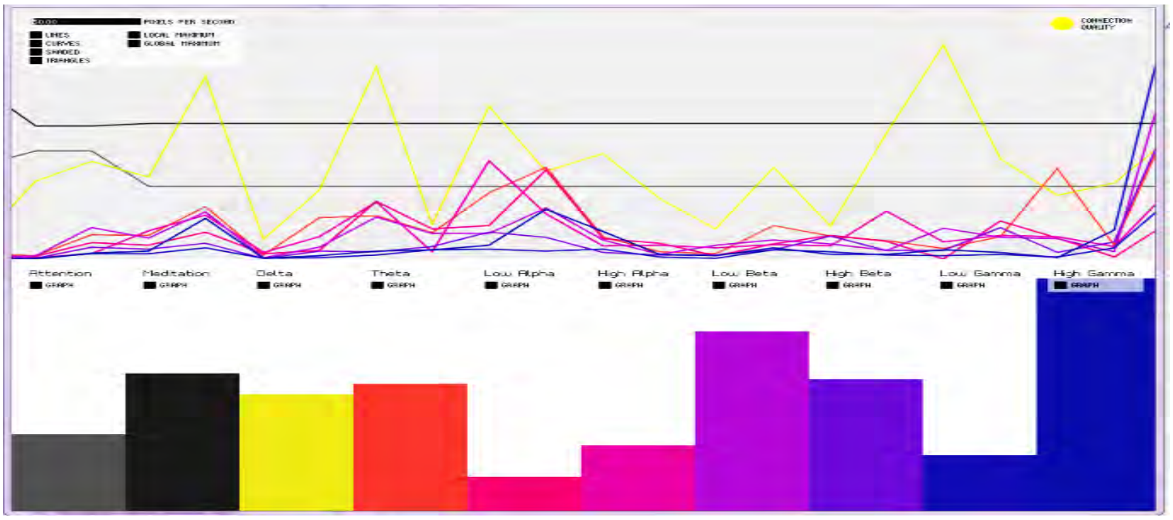


Figure 7-15: Monitoring Mental Load and Cognitive Strategy

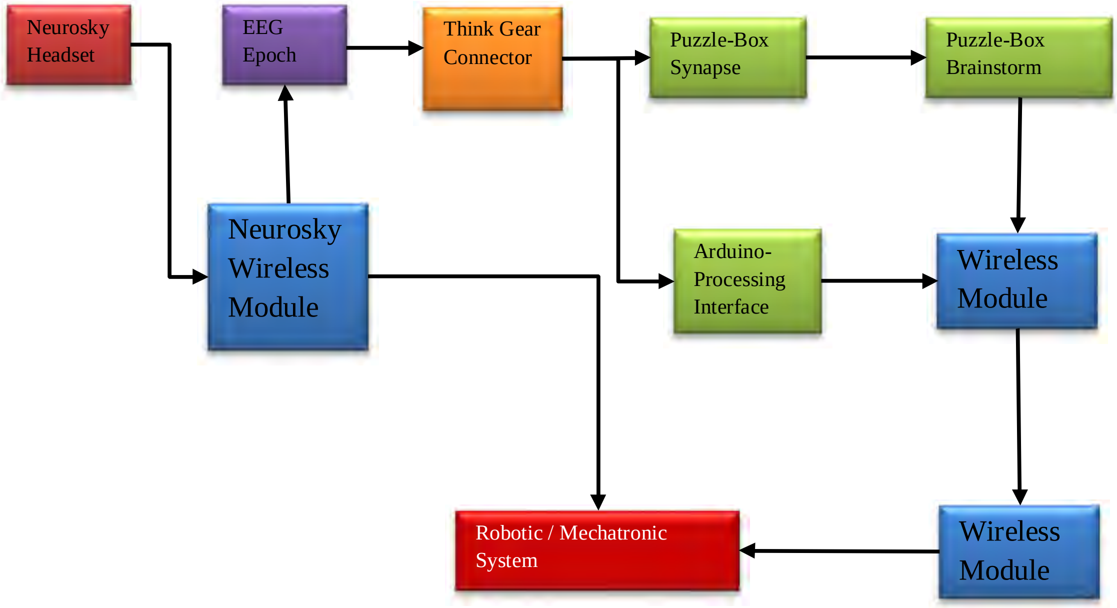


Figure 7-16: Wireless EEG Autonomic Network Structure Model using Neurosky Headset

7.3.4 Application 5: Emotional Alertness Management

Emotional alertness management refers to stimulation, awakening, provocation and excitement management. The physiological and behavioural states of human beings to a considerable extent define the level of consciousness in human beings. Daytime sleepiness and the ability of not being alert are problems associated with low emotional stimulation. Fatigue may also be experienced by individuals in the work environment due to depletion of mental capacity. In as much as daytime exposure of employees to higher illumination improves alertness; effective measuring of alertness cannot be achievable through traditional means. Emotional stimulation and management are key processes in human resource management and optimization. The applications of BCI technology can be extended in the use of non-invasive technique in monitoring the levels of employee alertness in the work environment. Human mind provocation can lead to an increase in memory capacity of an employee. The level of attention for a given task, through active emotional activation and BCI monitoring process increases the level of productivity in the available human capital in the organisation.

7.3.5 Application 6: Dependable Human-Machine Interaction

Developments into efficient interactions between humans and machines using BCI technology were proposed in this study. Dependable human-machine communication systems increase advancements in the functional requirements of robots in the manufacturing environment. The desire to have smart manufacturing environments and automation in every stage of the production line has increased the level of robot applications in these environments. The automation of daily activities, processes, functional tasks and high cost of human expertise are some of drivers in expanding robot applications in the manufacturing environment. Fatigue and stress are some of the problems associated with the reduction of human efficiencies with respect to precision, speed, and power towards the improvement of general wellbeing of humans. Assistive robots provide physical assistance to humans. In using dependable BCI systems, stress and fatigue are reduced while human efficiency and productivity are improved.

Invariably, human beings use their dynamic intelligence, experience, understanding and global knowledge of various processes to improve the execution of tasks. Due to Reliability issues in human-machine interactions, only dependable robot structures and systems are accepted for use in the augmentation of human and machine communication. The complexities that exit between the user and the robot are centred on the risks that are associated in the motion and execution collisions. Risks are also considered in the development human-machine interaction architecture. Miss representation of signals from EEG may cause the robot to transfer high power/energy or execute tasks which were not intended to be executed. Sending inappropriate EEG signal may cause serious injuries to humans and damage to the environment. Using highly classified EEG artefacts to send control commands will facilitate the development of safer human-machine architectures. Robot controlled commands powered by EEG artefacts can be adapted to indirect and direct force control of mechanisms with the manufacturing environment. Dependability of human-robot architectures powered by EEG signals has the following characteristics:

- Availability: There is always brain activity and as such there is no shortage of EEG artefact
- Safety: The absence of disastrous consequence to the user as the user is the generator of the EEG signals.
- Reliability: There is completion of control commands to specified satisfactory level
- Integrity: There is absence of system alteration once it is configured to a particular user.

To further understand the relationship between human and robot interaction while using BCI technology, it is presented that human-robot task collision metrics be considered in the application of BCI technology. This ensures that level of dependability of the BCI technology with respect to social cohesion, integration and interaction is fully established. Anthropic robotic design architecture provides the necessary interaction model in the development of dependable BCI system. This is illustrated in figure 7-17.

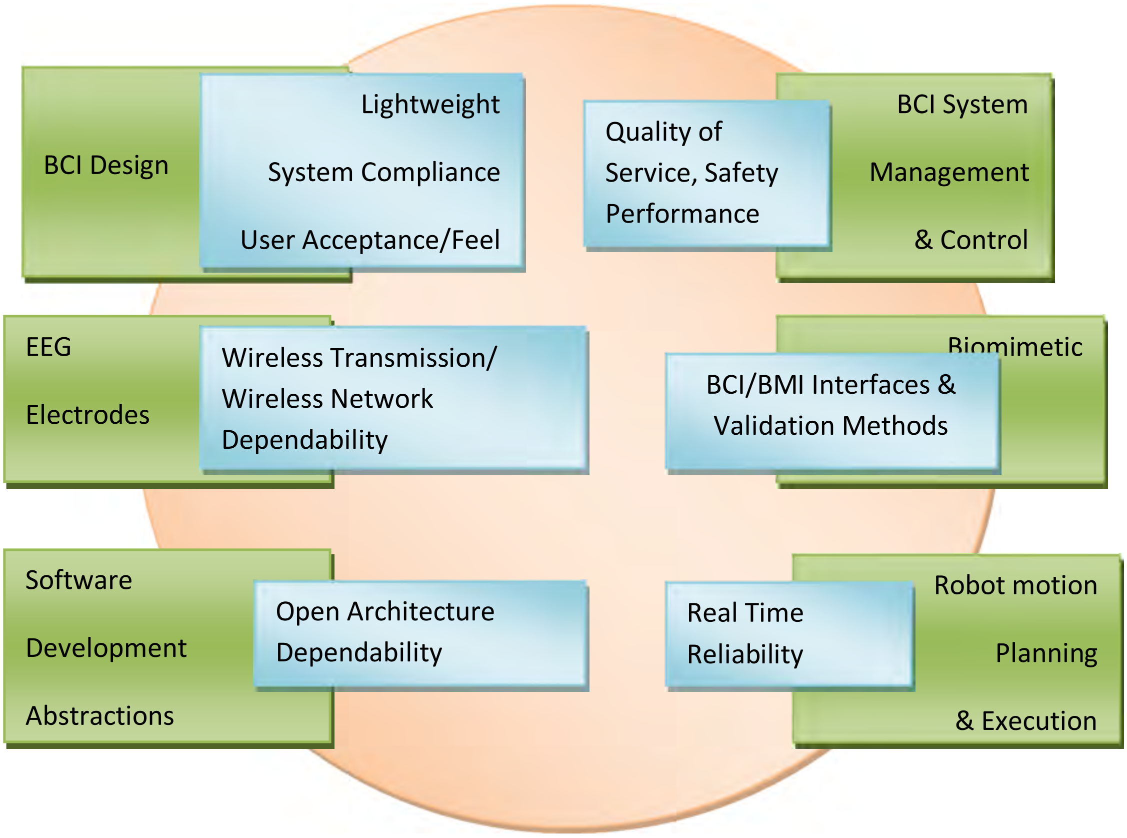


Figure 7-17: Human-Machine Interaction in Anthropic Domains.

7.3.6 Application 7: Space Vehicular Applications

In challenging and demanding environments such as space environment, space missions are one of the most challenging activities performed by human beings. Simple tasks such as picking and placing objects in a particular position become very challenging. The key factor in successful space missions is the ability of astronauts to make coordinated movements and to have high degree of motion precision. Here it is presented that BCI technology can provide augmented multitasking activities for the astronauts. In space, astronauts find it challenging to manually execute different tasks which may involve the use of both hands. Astronauts are constrained in their ability to manually direct commands to external devices and systems. BCI architecture can be structured such that it bypasses direct interaction with external devices. This can increase the astronaut’s degrees of freedom. The human brain has the ability to perform simultaneously different uncorrelated activities. An astronaut’s brain could be used in multitasking different functions in space given that the mechatronic system that can interpret EEG signals and can be fully exploited. EEG signals from the astronaut could also be used to monitor the health and stress level of the astronaut during each stage of space preparation and mission. Communication could directly be sent straight from the brain to ground station on earth, or to space robots. BCI technology can be useful in intra-vehicular and extra-vehicular communication processes.

7.3.7 Application 8: Unique RFID Packets

Radio Frequency Identification Technology (RFID) plays an essential role in BCI technology development. RFID can be used for transmission of EEG artefacts. Communication from the brain to the robot or any electronic device can be effectively transmitted with the use of wireless network system. Using RFID to develop EEG wireless network provides the advantage of not restricting the user to a particular location and position. Wireless network space confinement can be managed effectively with other wireless network components such as routers of specific configuration. Specific EEG artefacts can be implemented for use in developing specific RFID network packet data with unique identification to prevent network interference. Amongst other functions, the RFID network can provide data packet storage support in shared wireless network configuration. Unique RFID packets from EEG artefacts provide unique network tags for controlling devices.

7.3.8 Application 9: Augmented Cognition Technology

EEG formed the basis in the implementation of human cognition technology. In the present state of advancement in the development of BCI technologies, human cognition augmentation into various electronic systems is paving the way in creating smart products and robots. Behavioural data monitored and classified using EEG signals as the basis of analysis has the crucial application in detecting, categorizing images and the presentation time of events and activities.

7.3.9 Application 10: Marketing and Advertisement Management

Neural activity and neural firings are events indicating brain activity in human beings. With the use of BCI technology and fMRI, neural activity are accurately investigated and measured. Marketing and advertisements appeal to the human mind and increases the level of awareness, alertness and emotional stimulation. The monitoring of neural firings and brain activity during an advertisement and marketing exercise assists in determining the effects of these adverts and marketing gimmicks on human emotional intelligence. The areas and sections of the brain that are activated by a piece of advert could be monitored in order to make improvements on the advert. The level of excitement and happiness for a given marketing process provides the necessary feedback on the quality, effect of the advert and marketing process. BCI technology could also be used to provide information on the subconscious effects of marketing advertisement on human beings. Information from cognitive processes provides indications on levels of interests and business acumen. Entrepreneurial opportunities could be identified through human behavioural monitoring and marketing management.

7.3.10 Application 11: Universal Input System

Various input devices such as the mouse and keyboard have been the traditional modes of input and computing service process. Recent advancements introduced the use of touch screens as modes of inputs into the computer, electronic devices and computing devices. Various techniques are currently being investigated on ways of reducing cognitive load while using BCI technology as the input service to various technologies. BCI technology through specific EEG artefact extraction can be implemented as a gaze detector when input is to be made in various electronic gadgets. The eye-gaze system provides input methods for writing, typing and selection of item on the computer and other electronic devices. Results from measuring EEG power spectral densities with the combination of other sensing technologies can provide a new technique of providing input to electronic devices by gazing at the devices. Biometric communication and the use of BCI technology as the universal computing service for future technologies are possibilities that are imminent. BCI technology brings the control of complex smart environments closer to an individual's specific needs through use of intelligent graphic user interfaces.

7.3.11 Application 12: Hybrid Flexible Automated Communication Systems

Smart EEG-based framework for hybrid flexible automated communication in an advanced manufacturing environment breaks new ground in the present day communication system. Over the years, the manufacturing environment has been improved considerable with various advanced technologies and communication systems in creating sustainable environments for manufacturing and growth. Various factors are considered as the driving factors for technological improvements in the manufacturing environments. Communication, the critical element present in various technological systems has various dimensions for integration in smart machines. Integration of hybrid information from source to sink through an efficient communication system for systematic decision-making creates reconfigurability in smart machines. Communications to agile and reconfigurable machines are underpinned in their modular levels, machine-human information control system, and open architecture command control system. Centralised and sequential manufacturing control system commands for mechanism control traditionally have been found to have some bottle necks in networked manufacturing architectures. Integration and control through smart communication system based on EEG signals provide real-time control commands for automations with smart machines in the manufacturing environment. Using EEG as the smart communication protocol for automation and control of smart machines provides the manufacturing environment with high-level control systems. Low-level and high level control systems are seamlessly integrated using hybrid automated communication system flagged by EEG signal.

7.4 Summary

The application of EEG artefact identification, extraction and classification in controlling a robotic hand was presented in the chapter. The various applications of EEG data in BCI and BMI technology have been shown to be valuable technology in various mechatronic system applications. The practicality and implementation of EEG data in the various technologies requires different complexity and integration levels. Technology harmonization through EEG data as the primary control signal has expanded the frontiers of BCI and BMI technology and its application thereof. The use of visual feedback system provided useful validation methodology in the development of BCI technology. The applications presented in the chapter created avenues for breaking new frontiers in BCI technology development and applications.

CHAPTER EIGHT

Conclusions and Future Work

8.1 Conclusions

Background information and progressions made in the use of brain-imaging techniques, neural signal processing and cognitive neuroscience was introduced in chapter 1. The importance on how EEG provided mankind the unique capacity to observe and integrate feedback neuro-control system directly with human brain activity was also presented. In chapter 2, the comprehensive brief on the EEG, EEG activity types and generation were highlighted. The contingent negative variation of EEG signal property was used to establish the artefacts that are useful to perform independent component analysis on EEG signal and further analysis of EEG signals presented in chapter 5. The separation of EEG artefact through EEG data analysis and evaluation of EEG signals facilitated the extraction and classification of EEG signals for use in radial basis function analysis and implementation in the RBF network. Modelling the biological neural system as an artificial neural system created the avenue for exploitation of EEG signal properties for use in robot control commands. The chapter also presented the possibilities of using invasive or non-invasive brain computer interfaces in semi-autonomous control. The chapter discussed vital information which led to selection of non-invasive EEG measuring technique in the study. In chapter 3, the decoding and encoding of EEG signal was discussed and presented. The EEG encoding and decoding process made use of the Integrate-And-Fire (IAF) and the Asynchronous Sigma-Delta Modulator (ASDM). Burg's algorithm was used to determine estimates of model coefficients and Levinson-Durbin algorithm was instrumental in segmenting EEG data for further analysis. The work presented in chapter 3 was performed in order to investigate and validate the performance of ASDM and IAF models in decoding EEG signal for the control of a robotic hand

The integration of wireless autonomic EEG neural network with action observation network was modelled and presented in Chapter 4. The wireless autonomic network system was modelled such the EEG data transmission is managed effectively across the wireless network. The work presented in chapter 4 was performed in order to develop the desired motor control codes for controlling the robotic hand using AON and investigate the performance of the wireless autonomic neural network in transmitting the motor control codes. In chapter 5 the fundamental technique implemented in the identification, extraction and classification of EEG signals required that mathematical models of observed EEG signals were generated to represent the data. Generative EEG model were used for EEG signal compression, EEG artefact pattern recognition and de-noising of EEG signal. The EEG signal applications and the importance of blind signal source separation techniques were discussed. In interactions where fatalities due to machine malfunction was very much prevalent, the development of qualitatively analysed methodology to assess an individual's cognitive responses was crucial to the survival of human beings interacting with machines in the world controlled by mechatronic systems. The qualitative analysis techniques presented in chapter 5 provided the platforms which were used to investigate the neurobiological data underlying the EEG brain dynamics of an individual in various cognitive load scenarios. The analysis demonstrated the possibility of detecting and analysing several streams of EEG signals that represents an individual's cognitive states and responses to events and tasks. The work presented in chapter 5 was performed in order to develop an efficient/integrated EEG artefact identification, extraction and classification system for the control of the robotic hand.

In chapter 6, neuro-symbolic behaviour language was developed and presented as the mechatronic system control language. This was used in programming the microcontrollers, and managing the overall technical communication process between the robotic hand, mechatronic system and human beings. The distributed intelligence processing system managed the use the of neuro-symbolic language communication transmission using the NSBL. The work presented in chapter 6 was performed in order to develop a specialised behaviour-based robotic hand control system which reacts to EEG artefacts. Chapter 7 presented results from controlling the robotic hand. Chapter 7 also presented further application of the EEG artefact identification, extraction and classification technology.

Comprehensive BCI system acknowledges the presence of brain activity and classified different brain signals and patterns associated with human movements, motions and gestures as well as movement attempts made by physically challenged and disabled persons. EEG artefact extracted from EEG signals for coordination, control of mechatronic and robotic systems has created more unique opportunities in the application of bio-signals in semi-autonomous control systems. EEG signal monitoring and analysis for example were instrumental in detecting the affective, expressive and cognitive states of an individual in the presence of various tasks necessary for evoking the signals. It can be concluded that current technological advancements in mechatronics, robotics, and the use of bio-indicators, bio-sensing and bio-monitoring systems increased the possibilities envisaged in robotic and semi-autonomous control systems. The adaptation of BCI technology in the modern day processes provided this study the opportunity to make contributions and create effective communication and control strategies. Through BCI, robots serve as social companions to those individuals who feel neglected and side-lined by the society. BCI technology provides an intelligent caring environment for its users as robots are able to use the expressive, affective or cognitive signals provided by their users for communication. BCI technology incorporated into structures as exoskeleton provides assistance and service to individuals who have lost their motor control.

8.2 Future work and Research

In extracting and classifying useful artefact for mechatronic system implementation, the interrelation between integrated and hybrid autonomic system requires further research. The extraction and representation of EEG artefact suitable for integration in adaptive embedded system technology using symbolic language or logical language are also areas that require further study. The management of EEG data using hybrid distributed data management systems integrated in enterprise wireless autonomic system will increase the mobility application of EEG data in robotics, mechatronics and BCI technology development and requires further research. The development of efficient augmentation algorithm towards the implementation of distributed intelligent processing system in classified mechatronics and robotics applications also requires further attention to detail.

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Appendix A

A-1 The RN-171-XV Wireless Module

The RN-171-XV wireless module runs on 802.11b/g wireless network protocol. The RN-171-XV architecture is based on roving networks architecture. It is equipped with TCP/IP wireless protocol, WEP, WPA-PSK and WPA2-PSK compliant. The data rate for the wireless modules is at 464Kbps over the UART. The module can be configured to use Wi-Fi or UART.

Figure A-1: The RN-171-Wirelss Module

A-2 Xbee-Pro Wireless Module

The Xbee-Pro wireless module has RF data rates up 200kps within 902 and 928 MHz frequency band. With the installation of very high gain antenna, the Xbee-Pro wireless module can transmit data up to 45km. it makes use of UART interface for data transmission. Data can be transmitted up 610m at 10Kps for normal indoor usage and 305m at 200kps for outdoor urban usage. With these characteristics, the Xbee-Pro was integrated in the design and modelling of the EEG autonomic wireless network.

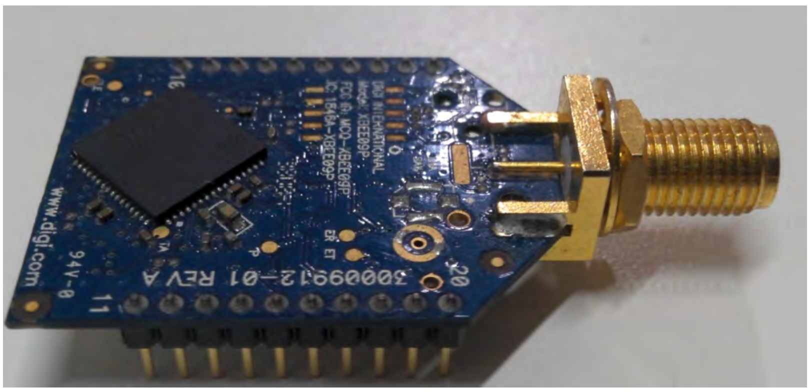

Figure A-2: The Xbee-Pro 900MHz Wireless Module

A-3 The Arduino Microcontroller Board and Wireless Shield

The arduino microcontroller serves as the computational brain for making logical comparisons and sequential operation in the broad integration and development of the BCI technology. The Ardunio microcontroller is equipped with ATmega328 chip with 14 digital input/output pins and 6 analog input pins. Integrated with the microcontroller is the wireless proto shield. This allows communication between the arduinio and the Xbee-Pro Module and the RN-171-Wirelss Module.

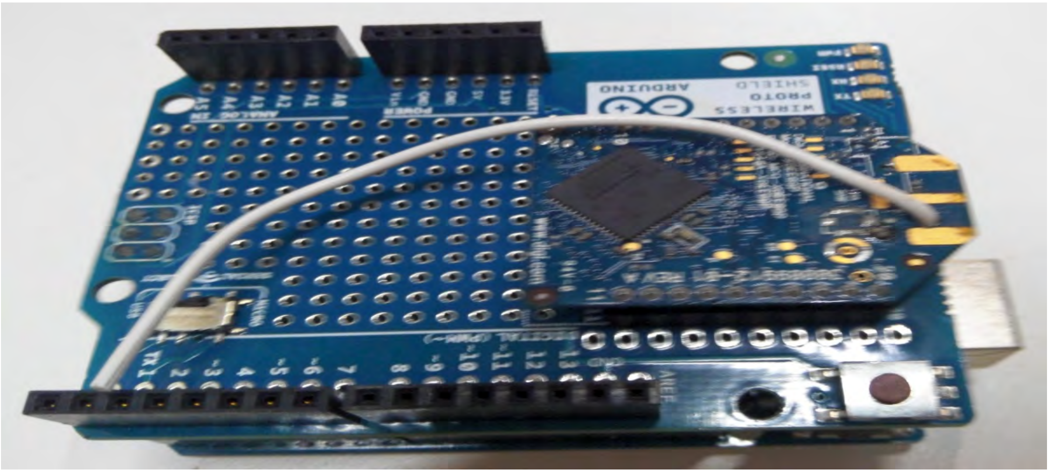

Figure A-3: The Arduino Uno and Wireless Proto Shield Setup.

In table A-1, the parameters in the Gaussian radial basis activation function are specified according to the dynamics of the neural network.

Table A-1: Neural Network Activation Functions

Activation functions	Formula $k = f(u)$	Derivatives $\frac{df(u)}{du}$
Sigmoid	$f(u) = \frac{1}{1 + e^{-u/T}}$	$f(u)[1 - f(u)]/T$
Hyperbolic Tangent	$f(u) = \tanh\left(\frac{u}{T}\right)$	$(1 - [f(u)]^2)/T$
Inverse Tangent	$f(u) = \frac{2}{\pi} tan^{-1}\left(\frac{u}{T}\right)$	$\frac{2}{\pi T} \cdot \frac{1}{1 + (\frac{u}{T})^2}$
Threshold /Network bias	$f(u) = \begin{cases} 1 & u > 0 \\ -1 & u < 0 \end{cases}$	Derivatives do not exist at $u = 0$
Gaussian radial Basis	$f(u) = exp[-\|u - m\|^2/\sigma^2]$	$-2(u - m) \cdot f(u)/\sigma^2$
Linear	$f(u) = au + b$	a

Appendix B

B-1 Multi-Layer Perceptron Training

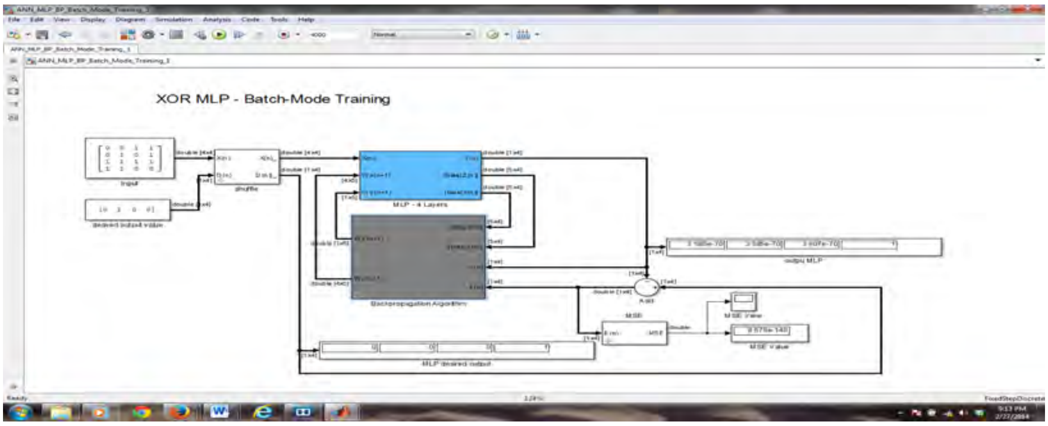

Figure B-1: MLP EEG Batch Training

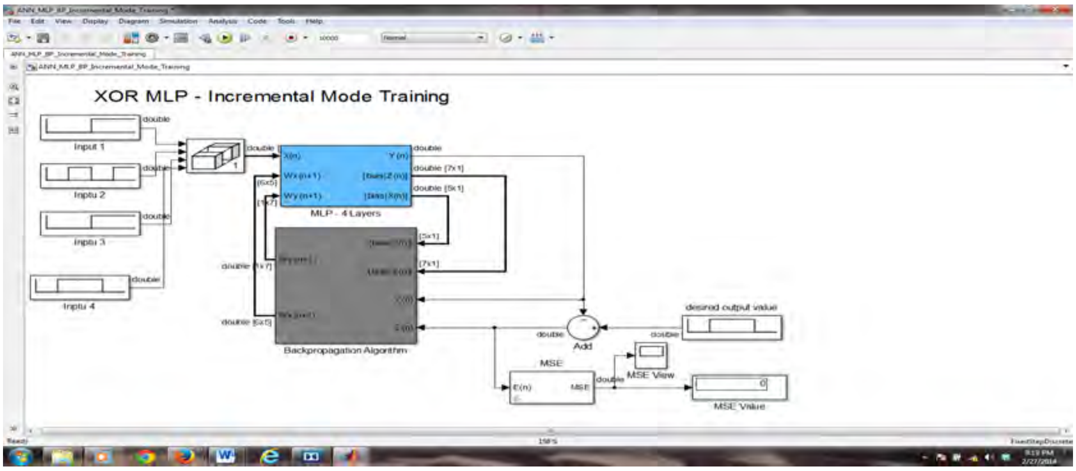

Figure B-2: MLP EEG Incremental Training

Appendix C

C-1 Emotiv BCI Development

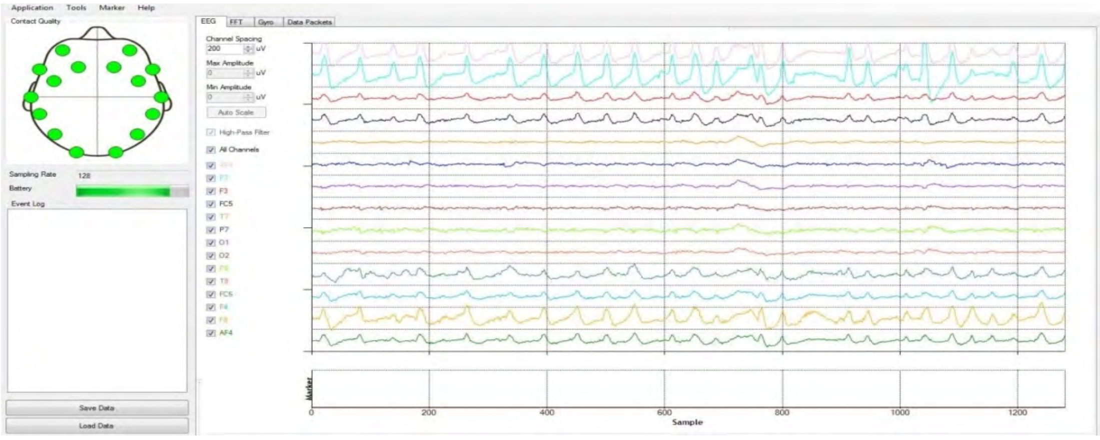

Figure C-1: EEG Data Analysis Using Emotiv Test Bench

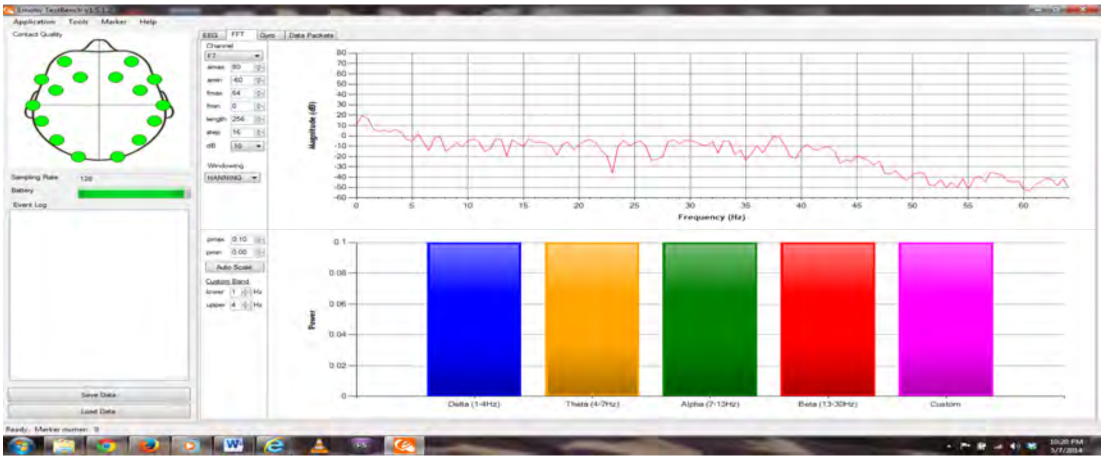

Figure C-2: FFT Analysis on Emotive Test Bench

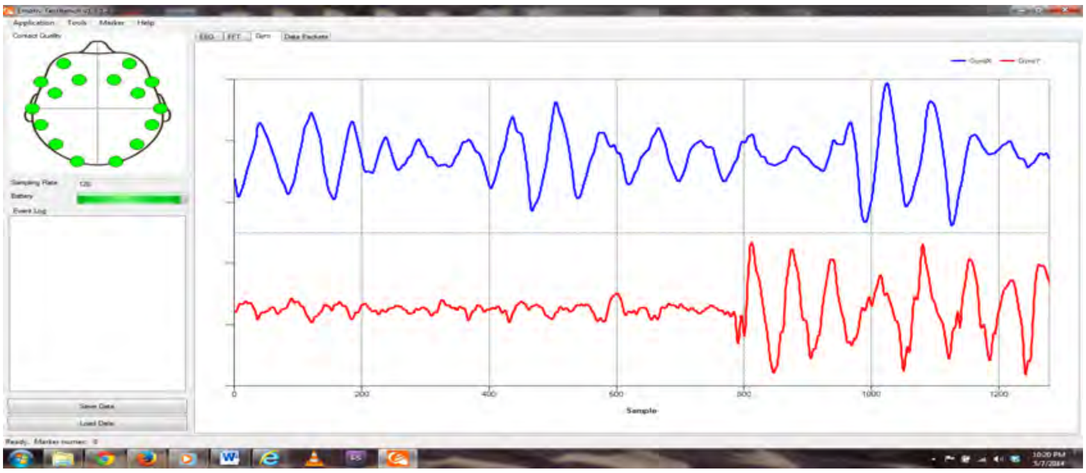

Figure C-3: Head Motion Monitor using Gyro on Emotiv Test Bench

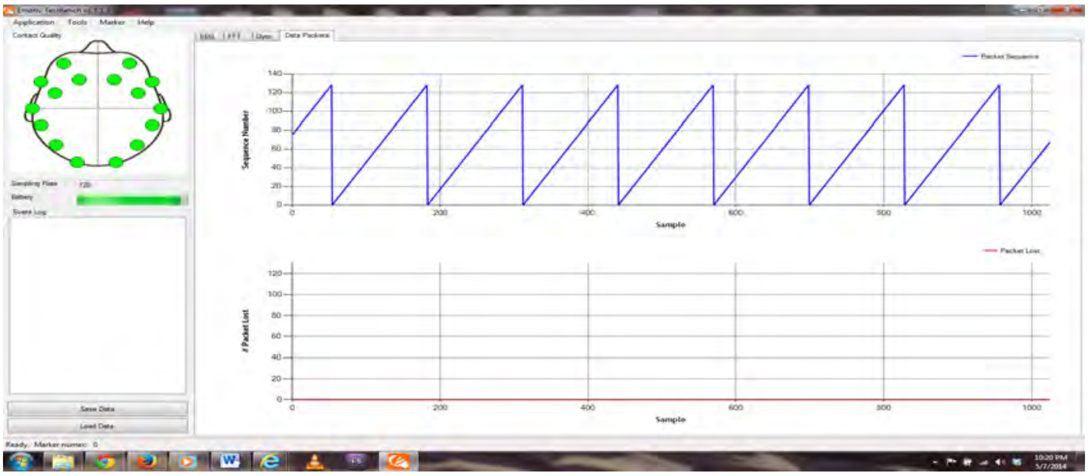

Figure C-4: EEG Data Rate Monitor on Emotiv Test Bench

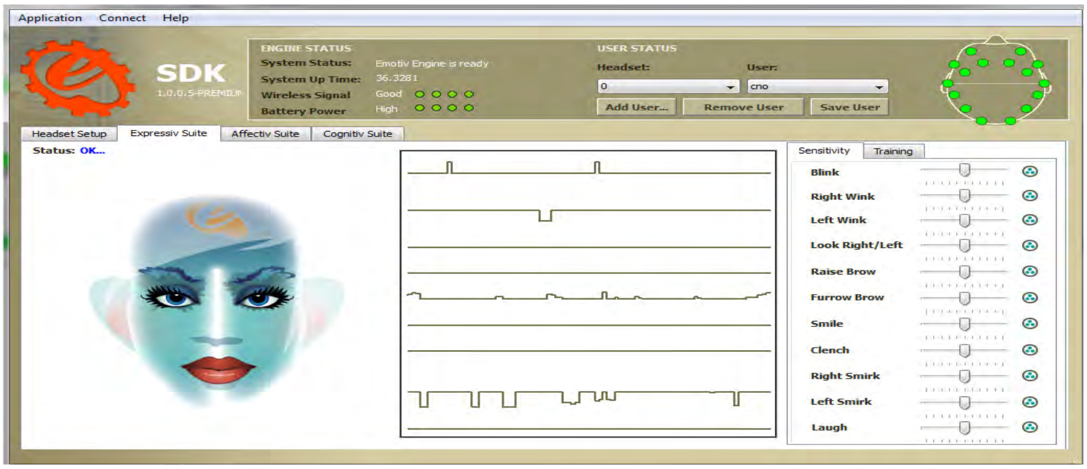

Figure C-5: EEG Headset Calibration using Expressive EEG signals

Figure C-6: EEG Headset Calibration using Affective EEG Signals

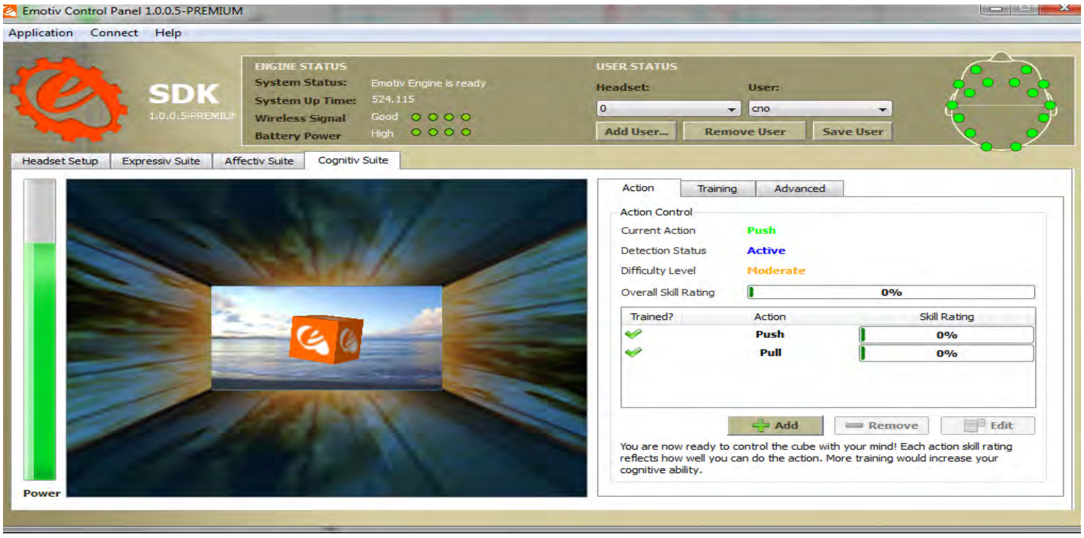

Figure C-7: EEG Headset calibration using Cognitive EEG Signals

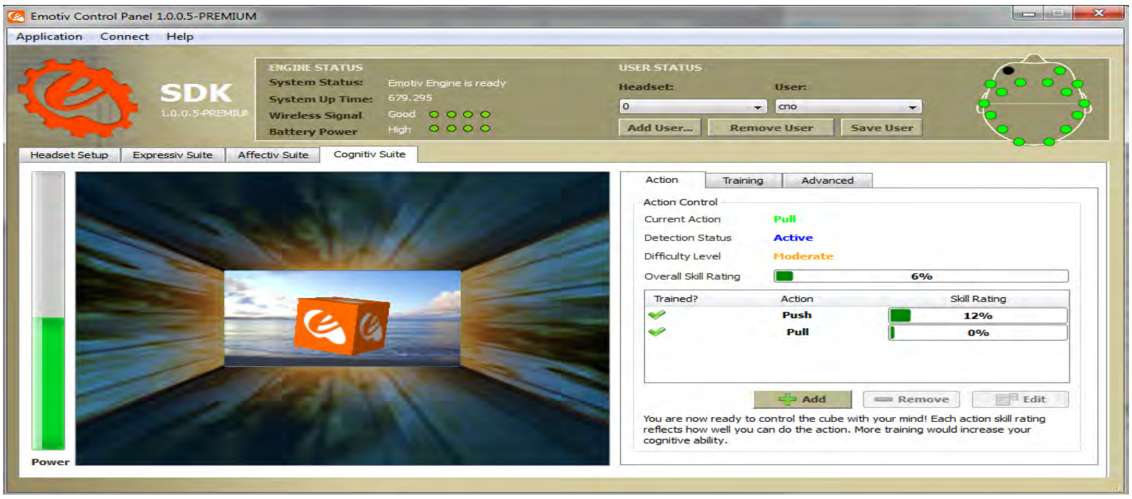

Figure C-8: Specific EEG Artefact Generation Training Using Cognitive Suite

Figure C-9: Mind your OSC Interface for EEG data

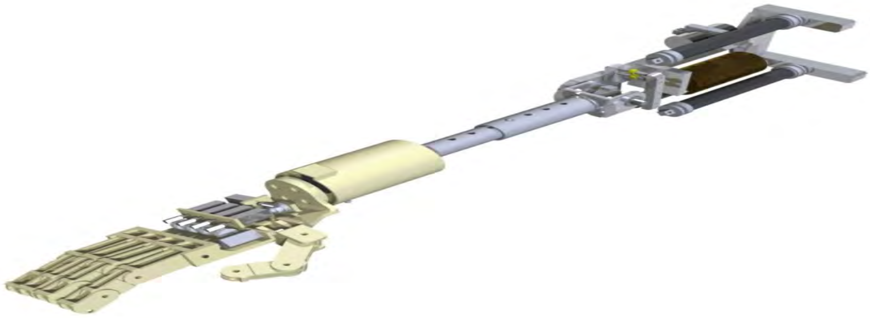

Figure C-10: Mechatronic Arm

Table C-1: Robot Motion Command Addresses

COGNITIVE ADDRESSES	AFFECTIVE ADDRESSES	EXPRESSIVE ADDRESSES
/COG/Neutral	/AFF/Engaged/Bored	/EXP/WINK_LEFT
/COG/PUSH	/AFF/Excitement	/EXP/WINK_RIGHT
/COG/PULL	/AFF/Excitement Long Term	/EXP/BLINK
/COG/LIFT	/AFF/Meditation	/EXP/LEFT_LID
/COG/DROP	/AFF/Frustration	/EXP/RIGHT_LID
/COG/LEFT		/EXP/HORIEYE
/COG/RIGHT		/EXP/VERTEYE
/COG/ROTATE_LEFT		/EXP/SMILE
/COG/ROTATE_RIGHT		/EXP/CLENCH
/COG/ROTATE_CLOCKWISE		/EXP/LAUGH;
/COG/ROTATE_COUNTER_CLOCKWISE		/EXP/SMIRK_LEFT
/COG/ROTATE_FORWARD		/EXP/SMIRK_RIGHT
/COG/ROTATE_REVERSE		/EXP/FURROW
		/EXP/EYEBROW

Table C-2: Robotic Hand Motion Execution

COGNITIVE ADDRESSES	ROBOT MOTION EXECUTED
/COG/PUSH	EXTEND THE ROBOTIC HAND FORWARD
/COG/PULL	RETRACT THE ROBOTIC HAND BACKWARDS
/COG/LEFT	TURN THE WRIST TO THE LEFT
/COG/RIGHT	TURN THE WRIST TO THE RIGHT
/EXP/WINK_LEFT	MOVE THE ROBOTIC ARM TO THE LEFT
/EXP/WINK_RIGHT	MOVE THE ROBOTIC ARM TO THE RIGHT

Appendix D

D-1 Neurosky-Puzzlebox Brainstorm BCI Development

Figure D-1: Neurosky E-Sense Monitor

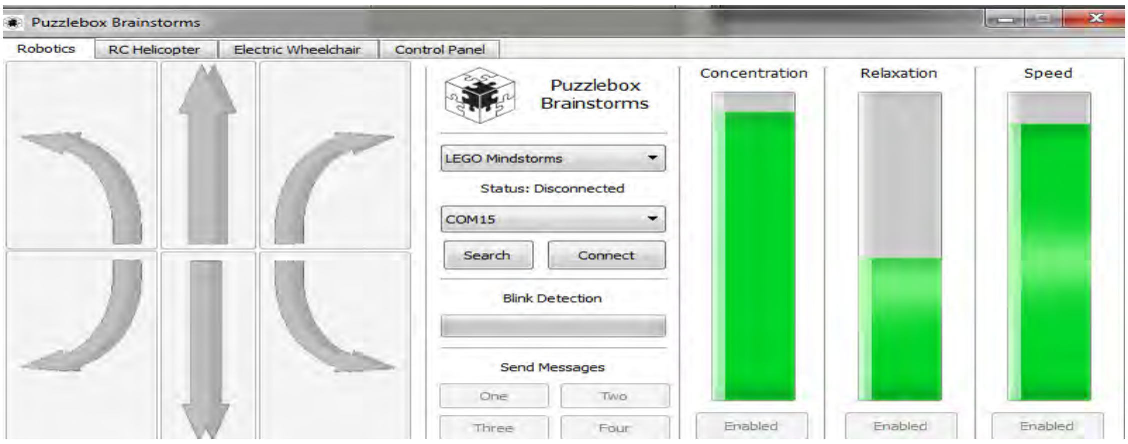

Figure D-2: Setup for Robotic Control Command using PuzzleBox Brainstorms

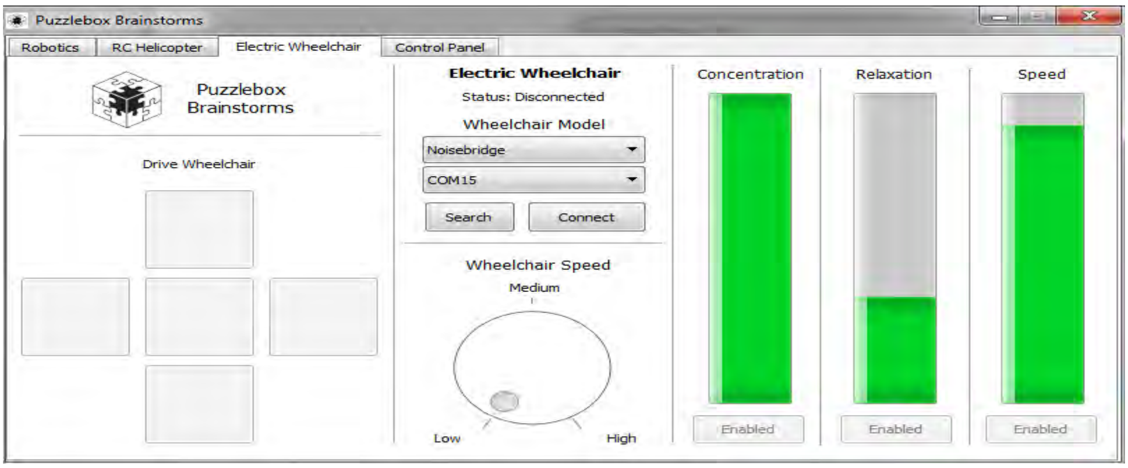

Figure D-3: Setup for Wheel Chair Control Command using PuzzleBox Brainstorms

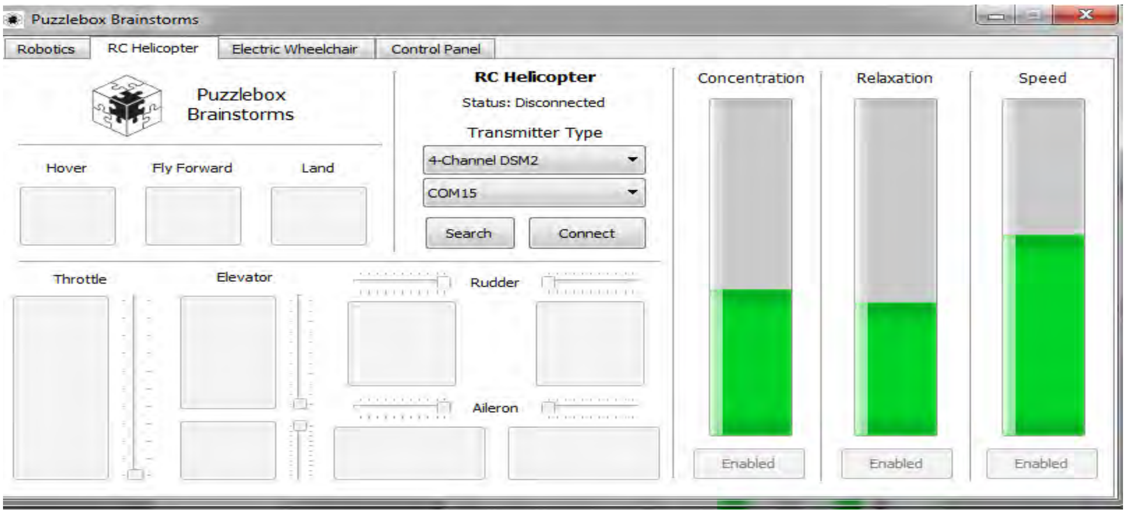

Figure D-4: Setup for RC Helicopter Control Command using PuzzleBox Brainstorms

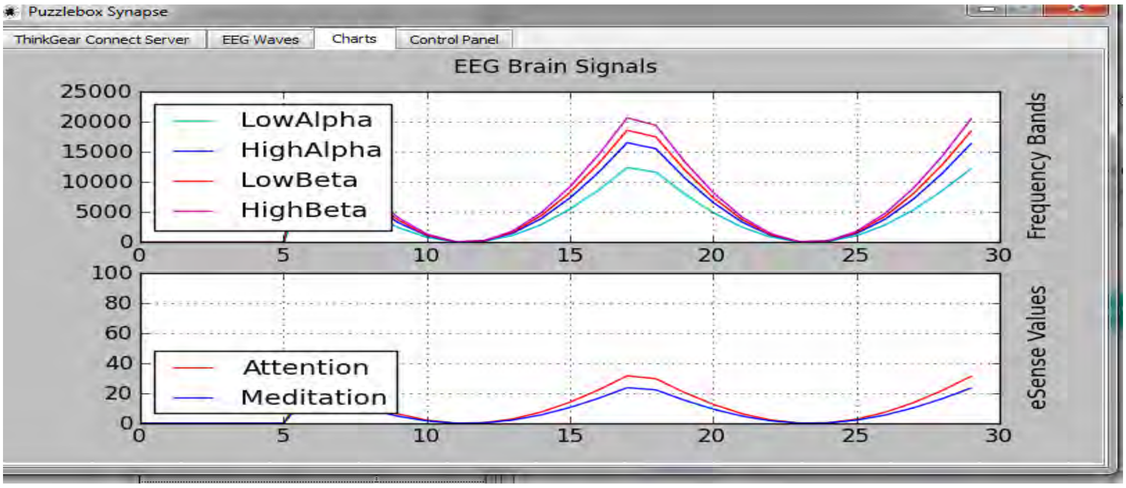

Figure D-5: Monitoring EEG Data using PuzzleBox Synapse

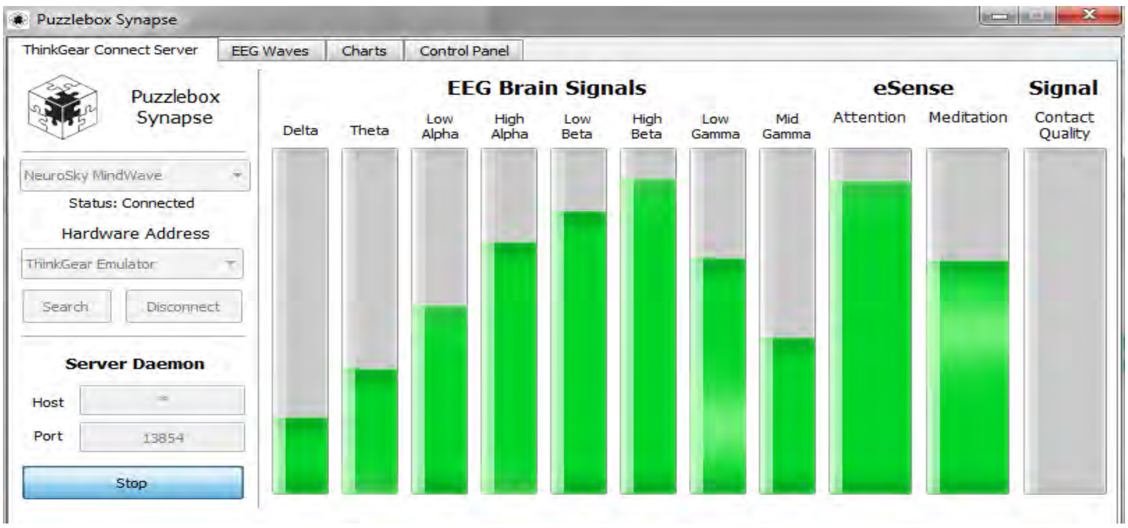

Figure D-6: Simulated EEG Signal using PuzzleBox Synapse

Appendix E

E-1 Derivation of Burg's Algorithm Parameter Estimate μ

$$y_n = -\sum_{i=1}^{k} a_i x_{n-i} \quad \text{(E-1)}$$

for $n \in [\![k, N]\!]$

$$z_n = -\sum_{i=1}^{k} a_i x_{n+i} \quad \text{(E-2)}$$

for $n \in [\![0, N-k]\!]$

The error between the original discrete EEG data and the approximated EEG data are reduced by F_k for the forward linear process and B_k for the backward linear process.

$$F_k = \sum_{n=k}^{N} (x_n - y_n)^2 = \sum_{n=k}^{N} \left(x_n - \left(-\sum_{i=1}^{k} a_i x_{n-i}\right)\right)^2 \quad \text{(E-3)}$$

$$B_k = \sum_{n=k}^{N} (x_n - z_n)^2 = \sum_{n=0}^{N} \left(x_n - \left(-\sum_{i=1}^{k} a_i x_{n+i}\right)\right)^2 \quad \text{(E-4)}$$

The error reduction process uses the autocorrelation or covariance method which was unstable for numerical computations. The Burg's approach to error reduction provides the robust and desirable method. Burgs method minimizes and summarizes the total sum of errors introduced in equation (E-3) and equation (E-4). Defining $a_0 = 1$ yields:

$$F_k = \sum_{n=k}^{N} \left(a_0 x_n + \sum_{i=1}^{k} a_i x_{n-i}\right)^2 = \sum_{n=k}^{N} \left(\sum_{i=0}^{k} a_i x_{n-i}\right)^2 = \sum_{n=k}^{N} \left(f_k(n)\right)^2 \quad \text{(E-5)}$$

with

$$f_k(n) = \sum_{i=0}^{k} a_i x_{n-i} \quad \text{(E-6)}$$

$$B_k = \sum_{n=0}^{N-k} \left(a_0 x_n + \sum_{i=1}^{k} a_i x_{n+i}\right)^2 = \sum_{n=0}^{N-k} \left(\sum_{i=0}^{k} a_i x_{n+i}\right)^2 = \sum_{n=k}^{N} \left(b_k(n)\right)^2$$

with

$$b_k(n) = \sum_{i=0}^{k} a_i x_{n+i} \quad \text{(E-7)}$$

Parameter estimate μ is derived from minimisation of $F_{k+1} + B_{k+1}$ where

$$F_{k+1} + B_{k+1} = \sum_{n=k+1}^{N} \left(f_{k+1}(n)\right)^2 + \sum_{n=0}^{N-k-1} \left(b_{k+1}(n)\right)^2 \quad \text{(E-8)}$$

$$f_{k+1}(n) = f_k(n) + \mu b_k(n-k-1) \quad \text{(E-9)}$$

$$b_{k+1}(n) = b_k(n) + \mu f_k(n+k+1) \quad \text{(E-10)}$$

Setting the derivative of μ to zero, adjusting indices and bounds yields μ

$$\mu = \frac{-2 \sum_{n=0}^{N-k-1} f_k(n+k+1) b_k(n)}{\sum_{n=k+1}^{N} f_k(n)^2 + \sum_{n=0}^{N-k-1} b_k(n)^2} \quad \text{(E-11)}$$

Using burg's recursive manipulations D_k of μ is presented as:

$$D_k = F_k - f_k(k)^2 + B_k - b_k\,(N-k)^2 \quad \text{(E-12)}$$

$$D_{k+1} = F_{k+1} - f_{k+1}(k+!)^2 + B_{k+1} - b_{k+1}\,(N-k-1)^2 \quad \text{(E-13)}$$

Expanding the squares, updating indices and factorising yields

$$D_{k+1} = (1-\mu^2)D_k - f_{k+1}(k+1)^2 - b_{k+1}(N-k-1)^2 \quad \text{(E-14)}$$

The parameter estimate μ is given as:

$$\mu = \frac{-2 \sum_{n=0}^{N-k-1} f_k(n+k+1) b_k(n)}{D_k} \quad \text{(E-15)}$$

Appendix F

F-1 EEG Data Parameter Estimate Using Levin-Durbin Algorithm

$$E = \sum_{n=-\infty}^{\infty} \left(y_n - \left(- \sum_{i-1}^{k} a_i y_{n-i}\right)\right)^2 = \sum_{n=-\infty}^{\infty} \left(y_n + \sum_{i=1}^{k} a_i y_{n-i}\right)^2 \quad \text{(F-1)}$$

Setting $a_0 = 1$ simplifies E to

$$E = \sum_{n=-\infty}^{\infty} \left(\sum_{i=0}^{k} a_i y_{n-i}\right)^2 \quad \text{(F-2)}$$

In order to minimise the error in the parameter estimation, partial derivatives of E are calculated and the minimum for E equated to zero for $j \in [\![1, k]\!]$. This yield

$$\frac{\delta \sum_{n=-\infty}^{\infty} \left(\sum_{i=0}^{k} a_i y_{n-1}\right)^2}{\delta a_j} = \sum_{n=-\infty}^{\infty} \frac{\delta \left(\sum_{i=0}^{k} a_i y_{n-i}\right)^2}{\delta a_j} = \sum_{n=-\infty}^{\infty} 2 y_{n-j} \left(\sum_{i=0}^{k} a_i y_{n-i}\right) = 0 \quad \text{(F-3)}$$

Representing the system of EEG signals by the matrix M having $K + 1$ columns and k rows; the coefficients A_k are determined by solving $MA_k = 0$. The generic solution to the system computes A_{k+1} as the function of N_{k+1}, E_k, A_k. Therefore,

$$a_1 = -\frac{R_1}{R_0} \quad \text{(F-4)}$$

$$E_1 = R_0 + R_1 a_1 \quad \text{(F-5)}$$

For the signal matrix size, k

$$\begin{bmatrix} R_0 & R_1 & \cdots & R_k \\ R_1 & R_0 & \cdots & R_{k-1} \\ \vdots & \vdots & \ddots & \vdots \\ R_k & R_{k-1} & \cdots & R_0 \end{bmatrix} \begin{bmatrix} 1 \\ a_1 \\ a_2 \\ \vdots \\ a_k \end{bmatrix} = \begin{bmatrix} E_k \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \text{(F-6)}$$

Expanding A_k with the zero vector U_{k+1} having reverse coefficients V_{k+1}. Using the linear combination $U_{k+1} + \lambda V_{k+1}$ and computing $N_{k+1}(U_{k+1} + \lambda)$ yields:

$$\begin{bmatrix} R_0 & R_1 & \cdots & R_{k+1} \\ R_1 & R_0 & \cdots & R_{k-1} \\ \vdots & \vdots & \ddots & \vdots \\ R_{k+1} & R_{k-1} & \cdots & R_0 \end{bmatrix} \begin{bmatrix} 1 \\ a_1 + \lambda a_k \\ a_2 + \lambda a_{k-1} \\ \vdots \\ a_k + \lambda a_1 \\ \lambda \end{bmatrix} = \begin{bmatrix} E_k + \lambda \sum_{j=0}^{k} a_j R_{k+1-j} \\ 0 \\ 0 \\ \vdots \\ 0 \\ \sum_{j=0}^{k} a_j R_{k+1-j} + \lambda E_k \end{bmatrix} \quad \text{(F-7)}$$

$$\lambda = \frac{-\sum_{j=0}^{k} a_j R_{k+1-j}}{E_k} \quad \text{(F-8)}$$

$$A_{k+1} = U_{k+1} + \lambda V_{k+1} \quad \text{(F-9)}$$

$$E_{k+1} = E_k + \lambda \sum_{j=0}^{k} a_j R_{k+1-j} = (1 - \lambda^2) E_k \quad \text{(F-10)}$$

Table: F-1 –Nonlinear Optimization Algorithms

Algorithm	$\Delta \boldsymbol{W}(t)$	Discussion
Steepest Descend Gradient	$= \eta \boldsymbol{g}(t) = -\eta\, dE/d\boldsymbol{W}$	$\boldsymbol{g}$ represents the gradient vector, η represents the step size or learning rate, also known as the error back-propagation learning
Newton's Method	$= -\boldsymbol{H}^{-1}\boldsymbol{g}(t)$ $= -\left[\frac{d^2E}{d\boldsymbol{W}^2}\right]^{-1} (dE/d\boldsymbol{W})$	$\boldsymbol{H}$ represents the Hessian matrix.
Conjugate Gradient Method	$= \eta \boldsymbol{p}(t)$ where $\boldsymbol{p}(t+1) = -\boldsymbol{g}(t+1) + \beta \boldsymbol{p}(t)$	